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CLASSIFICATION OF COTTON AND SUGARCANE PLANTS ON THE BASIS OF THEIR SPECTRAL BEHAVIOR

MUHAMMAD SHAHZAD SHIFA[1], M. SHAHID NAWEED[2], MUHAMMAD OMAR[2], M. ZEESHAN JHANDIR[2] AND TANVEER AHMED[3]

[1]*Department of Physics, The Islamia University of Bahawalpur, Pakistan*
[2]*Department of Computer Science & IT, The Islamia University of Bahawalpur, Pakistan*
[3]*Department of Computer Science COMSATS, Institute of Information Technology, Abbottabad, Pakistan.*

Abstract

The study is about the classification of cotton (*Gossypium hirsutum* L.) and sugarcane (*Saccharum officinarum* L.) crops based on spectral behavior of their plants. The hand held ground based remote sensing optical Multispectral Radiometer MSR5 has been used for this purpose. MSR5 scans a scene and gives its digital representation in 5 separate spectral bands compatible with Landsat satellite images, so the study is also applicable to Landsat images. To judge the discrimination power of five spectral bands, used as features to represent the scenes, K-means algorithm is used for unsupervised clustering of reflectance sample data set. Computational and visualization results of clustering through K-means show that MSR5 scans are good candidates for classification purpose. Supervised classification is achieved using K-nn algorithm, and 98% accurate results of classification are achieved. Choice of MSR5 for crop classification is good for two reasons: the results are accurate and the technique is an efficient way to represent an image with only five real values covering a 1.5 square meter.

Introduction

Remote sensing works on the basic principle that every object (matter) absorbs, emits, transmits or reflects electromagnetic radiation (Campbell, 1996). This feature of a substance can be used as a distinct characteristic of that substance from its appearance point of view. This is the fundamental principle involved in all remote sensing devices to capture an image (Gibson, 2000). When light of different wavelengths falls on plants, they reflect it as a unique characteristic of these plants and know as a spectral behavior of these plants. This reflected portion can be used to estimate plant type, change in plant biomass, canopy, and plant growth (Campbell, 1996). This spectral behavior can be used in classifications of crops (Lillesand & Keifer, 2000). Plant light reflectance can be estimated by the method of multispectral radiometry in near-infrared and visible portion of electromagnetic spectrum (Trenholm *et al*., 1990).

Muderrisoglu *et al*., (2009) classified the trees on the basis of colour perceptions. It provided a good point to start the use of computer vision techniques to automate the classification of plants on the basis of colour perceptions realized through of sensors like MSR5. Misra & Wheeler (1978) has documented that Landsat satellite multispectral scanner (MSS) data can be used to classify any crop, due to temporal pattern changes in spectral response of plants. MSR can be used for canopy development (Heidmann *et al*., 2000), disease identification (Nilsson & Johnson., 1996), nitrogen and yield measurements (Xue *et al*., 2004). MSR5 is used, for the first time, in Pakistan to classify crops. It is hoped that the present work will provide an impetus for further research in the field of remote sensing linking computer aided approaches in the discipline of plant sciences.

Materials and Methods

A small study site located at latitude 29° 23′ N and longitude 71° 46′ has been selected at the agriculture farm, and some area near the agriculture farm owned by The Islamia University of Bahawalpur. Multispectral Radiometer MSR5 was used to scan cotton and sugarcane crops (which are shown in Figs.1 and 2).

Multispectral radiometer: It is a ground based hand held optical remote sensing Multispectral Radiometer (MSR), which has upward and downward facing sensors to measure simultaneously both incoming and reflected radiations from the target. It works on the basic concept that every object emits, absorbs, transmits or reflects electromagnetic radiation in a manner characteristic of the substance.

There are three different models of MSR as manufactured by CROPSCAN Inc., Rochester, MN, USA. These models differ with respect to their spectral wavelength regions, numbers of band and bandwidths as mentioned in Table 1. The instrument has been used for the measurements of weed effects (Adcock *et al*., 1998; Chang *et al*., 2002; Thelen & Lee, 2002), Vegetation cover estimations (Ma *et al*., 1996; Chen & Gillieson, 1998; Vrindts *et al*., 2003), yield and nitrogen evaluations (Dudka *et al*., 1998; Guan & Nutter, 2000; Ma *et al*., 2001; Clay *et al*., 2002; Doraiswamy *et al*., 2002; Ma *et al*., 2005) and disease estimations (Green *et al*., 1998; Ewaldz, 2000). Work on influence of yellow color flowers by Nislson (1996) and spectral reflectance and pasture productivity relation has also been done by Tarr *et al*., (2005) using different models of CROPSCAN Inc MSR multispectral radiometers.

Model MSR5 was selected due to the fact that it works on 5 different portions including visible, near infrared and shortwave infrared of spectrum. Moreover, these bands are compatible with Landsat TM satellite bands, and hence its scan can be linked with Landsat satellite data.

It has five spectral bands and consist of blue-green (450 to 520 nm), green (520 to 600 nm), red (630 to 690 nm), near infrared (760 to 900) and shortwave infrared (1550 to 1750 nm). MSR5 can be useful in plant growth monitoring, visible bands regions for quantifying crops canopy features, near infrared band is especially useful for foliar disease in plants, shortwave infrared band region for water contents in plants.

Table 1. Features of different MSR models.

MSR models	No. of bands	Spectral range	Features
MSR16	16	450-1750 nm	Any 16 narrow bands in the given range
MSR8	8	450-810 nm	8 bands in VIS, and NIR
MSR5	5	450-1750 nm	5 Bands Compatible to Landsat

Fig. 1. Study area located at Agriculture Farm the Islamia University of Bahawalpur.

Fig. 2. Cropscan Multispectral Radiometer (MSR5) at study area.

Sample dataset: MSR5 scans were taken from fields (named as Field A, B, C, D, E, F and G). Each scan covers an area of diameter 1-1.5 m and height above the canopy was 0.5 m. The cotton plants were planted on 2.5 feet wide beds in such a way that they were separated by a distance of 9-12 inches on each side. The plants population in A, B, C, E, and G fields was about 30-35 thousands, and in D and F fields was about 20 to 25 thousands. Each field was about 1acre in size. The field A, B, C, E, and G had healthy plants, whereas fields D and F had unhealthy plants. The cotton plants in Field D were fully bloomed and those in the F field had shown few balls. Two sugarcane fields; Field H and Field I were situated near the Agriculture Farm (study area where cotton was planted) of the University. Both fields of sugarcane were two miles apart from each others.

Image representation and description using MSR5: A region comprises an object (like a crop or a human etc.) that may be represented by its boundary, and the boundary may be described by features such as its length and the number of concavities it contains. An external representation is selected when interest is on shape characteristics. An internal representation is selected when the principal focus is on regional properties, such as color and texture.

MSR5 represents an image or a scene by measuring the strength of reflectance (reflected energies). It describes reflected data region using five spectral bands covering 450 to1750 nm. Plant leaf shows some specific response for each band. Blue is absorbed, green is reflected, red is largely absorbed, near infrared is also reflected (more than green) and shortwave infrared is absorbed by water contents presented in plants leaf.

Table 2 shows cotton plant image and sugarcane plant images described by MSR5. Note that a complete scene is described by only five energy features i.e., five bands. So only five real valued pixels, describe the complete captured scene. In Matlab environment where a double pixel takes 8 bytes this captured image will take only 40 bytes. It is a real treatment for quick computations.

K-means clustering: K-means algorithm is used to check the discrimination power of scene features (five bands). Following are the steps of k-means algorithm:

1. Determine the K number of clusters
2. Find and calculate the centroid for computing distance
3. Find the minimum distances of objects from centorids

4. Classify the objects on the basis of minimum distance
5. Iterate the step 2, 3 and 4 until no object move to any class

Pattern recognition: Pattern classification is performed using K-nn algorithm for classification of scenes. Pattern recognition is concerned with the automatic detection or classification of objects or events into categories, especially by machine. For example, a pattern recognition system might automatically classify a crop whether it is healthy or unhealthy, or to classify an image indicating that it is a sugarcane image or cotton image or it is a bare land. The individual items, objects, or situations to be classified will be referred to as samples, or sometimes patterns. Pattern defined with features, and object features storing in rows are called pattern vectors. Instances of pattern vectors written in rows of a table represent specific objects and columns represent features of those objects. Pattern vector is a row (or column) vector of size 1xn (or nx1) where n represents number of features or attributes. Following is a pattern vector V of a cotton plant with 5 features showing energy reflectance by MSR5:

$$V = [4.3, 6.7, 7.06, 24.42, 18.93]$$

Categorization is the act of distributing things into classes of the same type. The measurements of properties used to classify the objects are called features and the types or categories into which they are classified are called classes. Pattern classification is organizing of pattern vectors of same type into different groups, sharing the same set of properties.

The K-nearest neighbor (K-nn) classifier: For supervised classification K-nearest neighbor algorithm (K-nn) algorithm is used. This is one of top ten machine learning algorithm (Xindong *et al*., 2007) that can classify different objects if the training dataset is appropriate. Following are the steps of K-nn algorithm:

1. Input K= (number of nearest neighbors) and dataset D with training column(s) T (showing categories of each training instance)
2. Find the distance between the query-instance (Q) with all the training instances in the dataset D
3. Get K instances from dataset D on the basis of first K minimum distances
4. Gather the category T of K nearest neighbors
5. Use majority vote of a category as the prediction value of the query instance

Results and Discussion

The current research focuses on reflectance dataset of MSR5 scans as mentioned previously. Each scan has been taken from 7 different fields named as (A. B, C, D, F and G) of cotton crop and 2 fields of sugarcane crops, named as field H and field I. Following steps are involved in the classifications of cotton and sugarcane crops.

Steps involved in classification

Sample dataset: Sample dataset S is collected in the span of 3 months at different times ranging 10:00 am to 4:00 pm and at different sun angles ranging from 40 to 70 degree. Fields of different conditions were scanned. To accommodate weather and time conditions, this span of three months is reasonable. MSR5 scans the input scene and store it into the memory of Data Logger Controller (DLC). From DLC data is taken into personal computer on excel sheets using the routines provided by the vendor of MSR5 equipment. 400 scans of 9 (7 fields of cotton and 2 fields of sugarcane) different fields with two types of crops, including cotton and sugarcane have been taken for this study.

Preprocessing of sample dataset: Some scans has been found at very low irradiance and at very large sun angle, so could not be used and has been discarded, resulting in 311 scans, as recommended by MSR5 vendor. Out of 311 scans of input dataset D, 20 samples are of bare land, 184 samples are of cotton and 107 samples are of sugarcane.

Validation of sample dataset D: Before applying classification on the input dataset blindly there is a need to judge the quality of input data set D. That is whether input dataset is reliable or not for classification purpose. For this purpose K-means clustering algorithm is used. In Table 3 results of K-means clustering on the sample dataset D are displayed at K=3. K=3 is chosen for clustering, because there are three objects instances in the sample dataset namely bare land, cotton and sugarcane scenes. Accuracy measure of clustered data indicates that supervised classification using K-NNwill give reliable results.

Figure 3 explains the clustering process visually. First k-means clustering is performed on the input dataset, then the input data with each cluster is shown in a different color using 3D scatter plot. As our actual data set dimension is 5D (5 bands) so to visualize data we take three bands for 3D plots in Figure 3(a) and 3(b). Figures 3(c) and 3(d) shows the silhouette plots, silhouette value for each point, is a measure of how similar that point is to points in its own cluster compared to points in other clusters, and ranges from -1 to +1. From the silhouette plot Figure 3(c), it is clear that second cluster is well separated from clusters 1 and 3, but there are some common points between clusters 1 and 2. Most of the points in cluster 1 and 3 are also distinct but negative values in cluster 3 indicate that there are points, which are not well separated. About 30% data points in cluster 3 are tentative towards cluster 1. Silhouette plots in Figures 3(c) and 3(d) show that data is well clustered for k=3 rather than some other k like k=4.

Accuracy of cotton and bare land instances in Table 3 indicates that, it is possible to work on classification task on the basis of input reflectance dataset. From the 3D scatter plots and silhouette plots of unsupervised clustered data, it is further illustrated that the input data set has distinct features (five bands) to classify the input scenes.

Training and testing datasets: As mentioned previously that input dataset has been taken over a period of 3 months, training and testing data sets have been prepared with a mix-up of all input scans at different times and dates. From the input dataset D 204 instances have been selected for training dataset T. Dataset T consists of 12 samples of bare land, 118 samples of cotton and 74 samples are for sugarcane. After choosing training data from D, remaining 107 instances were used for testing dataset V. Testing dataset V consists of 8 samples of bare land, 60 samples of cotton and 39 samples are for sugarcane.

Supervised classification: To classify an unseen instance into bare land, cotton or sugarcane it was decided to choose K-nn classification algorithm on the following bases:

1. K-nn is widely used supervised classification algorithm in many machine learning and pattern classification tasks (Xindong *et al*., 2007).
2. K-nn is a complementary approach for K-means clustering.

Table 4 shows good classification results achieved using K-nn algorithm at different k's using test dataset V.

Explaining the classification task by an example: Due to large size of input dataset D, 311 rows and 5 columns, a subset of D having 25 rows and 5 columns is taken to explain the computational work. Reduced dataset has 5 instances of bare land, 10 instances of cotton, and 10 instances of sugarcane scans.

First five columns in Table 6 viz., x1, x2, x3, x4 and x5 represents reflectance values at five bands separate, where x1 is reflectance at 485 nm spectral centered wavelength with spectral passband wavelength (450 to 520 nm) blue-green, x2 is reflectance at 560 nm with spectral passband (520 to 600 nm) green, x3 is reflectance at 660 nm with spectral passband (630 to 690 nm) red, x4 shows reflectance at 830 nm with spectral passband (760 to 900) near-infrared, and x5 shows the reflectance at 1650 nm spectral centered wavelength with spectral passband wavelength (1550 to 1750 nm) shortwave infrared.

Unsupervised clustering has been performed by using k-means clustering on the input dataset of 25 instances. Following Table 6 shows the results of Kmeans clustering at K=3. Note that all the instances of open land (first five) and cotton crop (row 6 to row 15) are correctly clustered but three instances of sugarcane are not classified properly. Column 6 shows the output of Kmeans and column 7 shows the expected outcome. Misclassified instances are highlighted by making values bold. 22 out of 25 instances are classified accurately hence 88% data instances are properly classified, showing that five features (x1 to x5) are faithful features and can be used to categorize unseen instances using K-nn algorithm.

The problem in hand is that we want to indicate that whether an image contains a crop of sugarcane or cotton or it represents a bare (open) land. Table 7 shows training instances with training column Train. Working of K-nn algorithm on reduced dataset is explained by considering the following query instance Q.

Query instance **(Q)** is:

Query = [3.6 5.54 5.42 22.28 14.67]

The steps of K-nn algorithm

Step 1: Let K=11 and D is training dataset (x1, x2, x3, x4 and x5) shown in first five columns of the Table 7.

Step 2: Calculate the Euclidean distance between the query-instance Q and all the training samples present in Table 7.

Step 3: Assign Rank according to ascending order of distances

Step 4: Select the category of nearest neighbors. Notice that All the rows where 2^{nd} last column in following table has No are not in K= 11 neighbors.

Step 5: Use simple majority of the category of nearest neighbors as the prediction value of the query instance. Out of 11 nearest neighbors 9 are cotton instances and 2 are sugarcane instances. We have 9 Cotton plants and 2 sugarcane plants in the count, since 9 > 2 then we conclude that query instance is included in cotton class.

Tables shows the percentage errors of classification of instances.

Table 2. MSR5 Image description of cotton and sugarcane plants.

Image type	485 nm	560 nm	660 nm	830 nm	1650 nm
Cotton	4.3	6.7	7.06	24.42	18.93
Sugarcane	4.17	7.98	6.21	36.68	15.46

Table 3. Reliability of sample dataset D.

MSR scan type	Total instances	Errors at K = 3	% Errors	Accuracy
Bare Land	20	0	0	100
Cotton	183	12	6.55	93.45
Sugarcane	108	48	44.44	55.56

Table 4. Total errors in different objects instances in the test data set V.

MSR scan type	Total instances	Errors at K = 9	Errors at K = 11	Errors at K = 15	Errors at K = 19	Errors at K = 25
Bare land	8	0	0	0	0	0
Cotton	60	2	2	1	1	1
Sugarcane	39	4	2	3	5	7

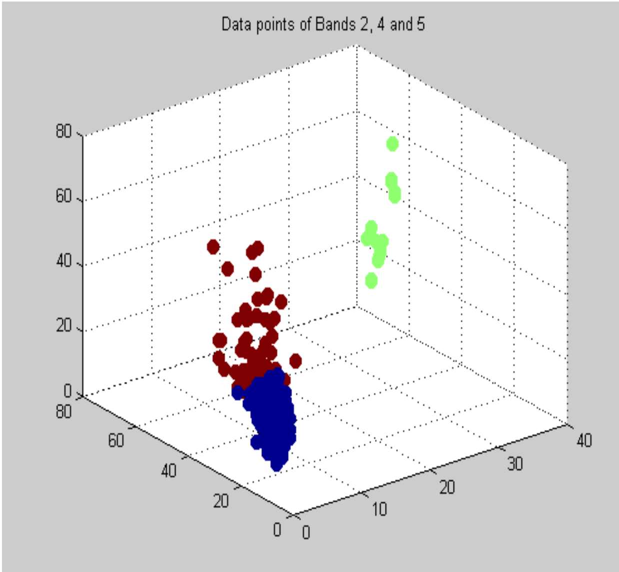

Fig. 3(a). Plot of Bands 2, 4 and 5 against 3 clusters (bare land, cotton and sugarcane).

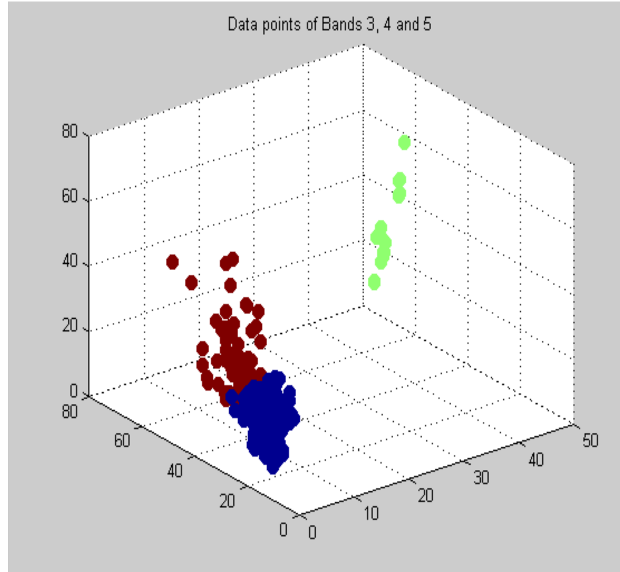

Fig. 3(b). Plot of Bands 3, 4 and 5 against 3 clusters (bare land, cotton and sugarcane).

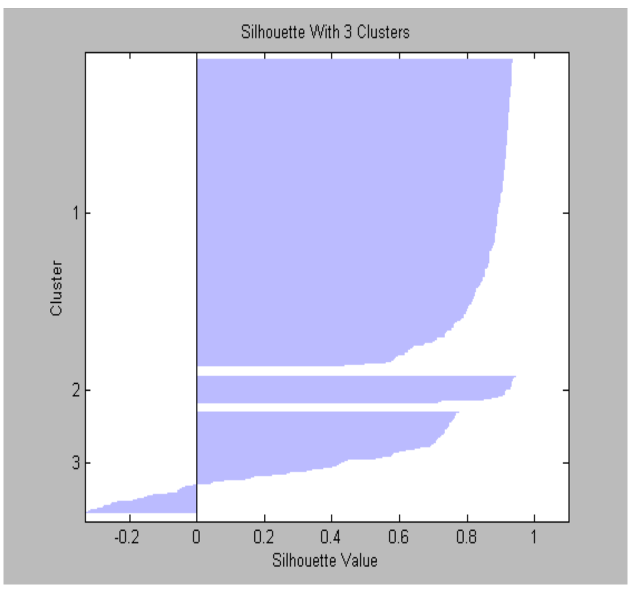

Fig. 3(c). Silhouette plot using K-means at k=3.

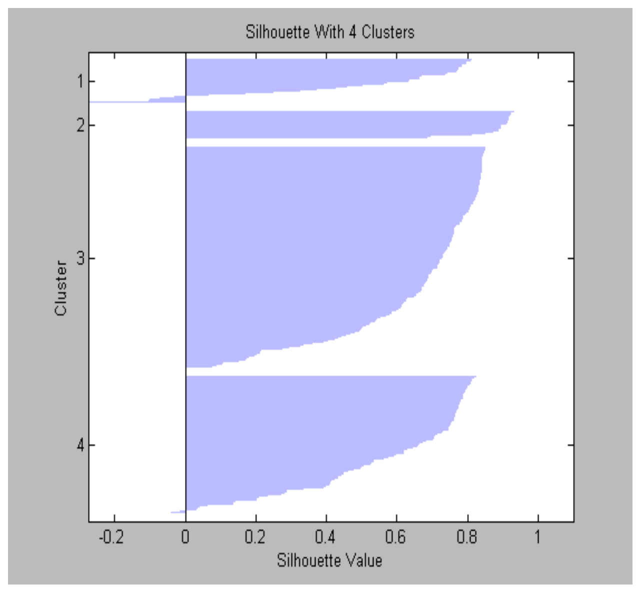

Fig. 3(d). Silhouette plot using K-means at k=4.

Table 5. Percentage errors of K-nn classification using test dataset V.

MSR scan type	% Errors at K = 9	% Errors at K = 11	% Errors at K = 15	% Errors at K = 19	% Errors at K = 25
Bare land	0	0	0	0	0
Cotton	1.9	1.9	0.9	0.9	0.9
Sugarcane	3.7	1.9	2.80	4.67	6.54

Conclusions

The study shows that MSR5 is a good choice for plants classification. Classification of cotton and sugarcane is achieved using supervised classification algorithm k-NN. Results in table 7 shows that raw reflectance data is a good choice for classification. For performance evaluation unsupervised clustering is used. Analysis shows that crops classification is working well at K=11 or at 15 for K-NNalgorithm. MSR5 has 5 bands which are compatible with bands of Landsat TM satellite and can be used to correlate the MSR5 data with Landsat data. So the current study is applicable on Landsat images also 98% accuracy and efficiency of classification shows that by using MSR5 we can automate analysis of crops in the agriculture country like Pakistan.

Table 6. Result of K-means algorithm.

x1	x2	x3	x4	x5	Clusters at K =3	Expected cluster
23.91	32.66	40.53	46.57	54.85	3	Open land
23.87	32.59	40.39	46.42	54.58	3	Open land
23.83	32.56	40.33	46.32	54.51	3	Open land
23.99	32.75	40.68	46.76	55.06	3	Open land
17.62	24.27	29.85	33.66	39.64	3	Open land
4.45	6.98	7.27	25.82	19.53	2	Cotton
4.48	7.01	7.27	26.11	19.56	2	Cotton
4.36	6.8	7.16	24.85	19.31	2	Cotton
4.3	6.7	7.06	24.42	18.93	2	Cotton
4.08	6.09	6.55	20.62	17.46	2	Cotton
4.17	6.28	6.73	21.65	18.25	2	Cotton
3.73	5.63	6.11	19.63	16.8	2	Cotton
3.69	5.54	6.01	19.36	16.43	2	Cotton
3.76	5.85	6.12	20.97	16.14	2	Cotton
4.12	6.65	5.93	25.38	16.32	2	Cotton
5.65	10.67	9.29	38.07	20.98	1	Sugarcane
4.2	8.04	6.57	30.37	15.07	1	Sugarcane
4.6	7.57	8	27.59	16.7	**2**	Sugarcane
4.46	7.56	5.69	29.98	12.04	1	Sugarcane
3.59	6.26	4.84	23.18	10.26	**2**	Sugarcane
4.15	7.3	5.73	26.36	11.93	**2**	Sugarcane
4.7	8.15	6.65	28.86	13.45	1	Sugarcane
4.52	8.57	6.27	30.71	13.63	1	Sugarcane
4.08	7.91	5.55	39.65	14.64	1	Sugarcane
4.23	8.24	6.07	38.79	15.01	1	Sugarcane

Table 7. Explanation of K-nn classification on reduced dataset.

x1	x2	x3	x4	x5	Training	Distance	Rank	K (=11) Nghb	Classification
23.91	32.66	40.53	46.57	54.85	Open land	4585.1391	24	No	
23.87	32.59	40.39	46.42	54.58	Open land	4541.024	23	No	
23.83	32.56	40.33	46.32	54.51	Open land	4523.1886	22	No	
23.99	32.75	40.68	46.76	55.06	Open land	4630.0263	25	No	
17.62	24.27	29.85	33.66	39.64	Open land	1897.2035	21	No	
4.45	6.98	7.27	25.82	19.53	Cotton	42.3698	11	Yes	Cotton
4.48	7.01	7.27	26.11	19.56	Cotton	44.9388	13	No	
4.36	6.8	7.16	24.85	19.31	Cotton	33.3273	10	Yes	Cotton
4.3	6.7	7.06	24.42	18.93	Cotton	27.2524	8	Yes	Cotton
4.08	6.09	6.55	20.62	17.46	Cotton	12.3495	4	Yes	Cotton
4.17	6.28	6.73	21.65	18.25	Cotton	15.8019	6	Yes	Cotton
3.73	5.63	6.11	19.63	16.8	Cotton	12.0605	3	Yes	Cotton
3.69	5.54	6.01	19.36	16.43	Cotton	11.9802	2	Yes	Cotton
3.76	5.85	6.12	20.97	16.14	Cotton	4.4887	1	Yes	Cotton
4.12	6.65	5.93	25.38	16.32	Cotton	14.0951	5	Yes	Cotton
5.65	10.67	9.29	38.07	20.98	Sugarcane	334.6365	20	No	
4.2	8.04	6.57	30.37	15.07	Sugarcane	73.5406	16	No	
4.6	7.57	8	27.59	16.7	Sugarcane	44.0943	12	No	
4.46	7.56	5.69	29.98	12.04	Sugarcane	71.0998	15	No	
3.59	6.26	4.84	23.18	10.26	Sugarcane	21.113	7	Yes	Sugarcane
4.15	7.3	5.73	26.36	11.93	Sugarcane	27.6502	9	Yes	Sugarcane
4.7	8.15	6.65	28.86	13.45	Sugarcane	54.3198	14	No	
4.52	8.57	6.27	30.71	13.63	Sugarcane	82.8963	17	No	
4.08	7.91	5.55	39.65	14.64	Sugarcane	307.582	19	No	
4.23	8.24	6.07	38.79	15.01	Sugarcane	280.8051	18	No	

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