DELINEATION OF DISEASED TEA PATCHES USING MXL AND TEXTURE BASED CLASSIFICATION

Rishiraj Dutta[a, *], Alfred Stein[a], N.R. Patel[b]

[a]Department of Earth Observation Science, International Institute for Geoinformation Science and Earth Observation ITC, 7500 AA Hengelostraat, Enschede, The Netherlands - (dutta13191@itc.nl and stein@itc.nl)
[b]Agriculture and Soils Division, Indian Institute of Remote Sensing (NRSA), Department of Space, Government of India, Dehradun-248001, Uttarakhand, India - nrpatel@iirs.gov.in

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ABSTRACT:

Recently, a rapid decline in the quality of Indian tea production has been observed due to the old age of the plantations, disease and pests infestations and frequent application of pesticides and insecticides. This paper shows an application of remote sensing and GIS technologies for monitoring tea plantations. We developed an approach for monitoring and assessing tea bush health using texture and tonal variations from Landsat, Aster and LISS III images. The Gray Level Co-occurrence Matrix (GLCM) categorizes the tea into healthy, moderately healthy and diseased tea. We observed from the study that the GLCM could be used for delineating the affected and non-affected tea patches at different resolutions.

1. INTRODUCTION

India continues to be the world's largest producer and consumer of tea. Due to increasing competition from countries like Sri Lanka, Kenya, China, Bangladesh and Indonesia, and problems in maintaining the quality, Indian tea yield has been witnessing a downward trend. Tea yield statistics show that tea plants start to produce tea leaves from approximately their third year onwards, maintain a steady increasing trend upto some 20 or 30 years of age, within which period they reach a peak in production during several years and then decline.

Remote sensing offers an efficient and reliable means of collecting the required information for mapping tea type and acreage. It also provides structural information on various aspects of vegetation health, as the spectral reflectance of a tea field varies with respect to the phenology, stage type and crop health. Thus, tea plantations could be well monitored and measured using multispectral sensors.

Information from remotely sensed data can be used as input into a Geographic Information System (GIS) or a similar cropping system. This can then be combined with ancillary data to provide information of ownership and management practices. Assessment of tea health, as well as early detection of crop infestations, is critical in ensuring good tea productivity. Stress associated with, for example, moisture deficiencies, insects, fungal and weed infestations, must be detected early enough to provide an opportunity for the planters to mitigate. To monitor this process effectively requires that remote sensing imagery is provided on a frequent basis.
Remote sensing has a number of attributes that lend themselves to monitoring tea bush health. Detecting damage and monitoring stress requires high-resolution imagery and multispectral imaging capabilities. A critical factor in making imagery useful to planters is a quick turnaround time from data acquisition to distribution of crop information. To receive an image that reflects crop conditions two weeks earlier neither helps real time management nor damage mitigation. Images are also required at specific times during the growing season, and on a frequent basis.

The tea industry in Assam grew in terms of acreage, but in the course of time it started facing many problems. The present crisis in the tea industry started in 1999, when drought during the early part of the season resulted into large production cuts. Year 2000 saw a marginal improvement in production but in the same time a sharp drop in prices throughout the year. Production in Assam in 2001 was low as compared to the national average. Export dropped by 27 million kg and Assam could export only 18 million kg of tea. It has been hypothesized that Assam is losing export due to increasing pest and disease occurrences, which are caused by maintaining an inferior production mix, the old age of tea plants, poor quality control at the processing level and economic factors like organization of small holder farmers and associated high costs of production, . A recurrent problem of tea gardens is pest infestation. Many tea gardens are affected by Helopeltis, Red Spider and Lopper attacks. Such infestations can possibly be timely monitored and assessed using remote sensing images.

The main objective of this study is to delineate disease and pests infested areas in tea gardens. To do so, the paper uses texture and tonal variations from satellite imagery of tea growing areas and investigate whether texture based classification could be utilised for disease and pests detection in tea plantation.

1.1 Review of Literature

Tea is a mono-cultured crop. It stands in field situation with little inter culture operation and no crop rotation. Such conditions ultimately lead to degradation of the soil environment either being physical, biological or chemical in

* Corresponding author.

nature. The mono-culture of tea reportedly causes a condition of improper soil functioning known as soil sickness (Barua, 1969).

Realizing the importance of tea growing from both a managerial and a commercial point of view, Tripathy et al predicted tea yield using remote sensing and GIS and other key parameters with a GIS. Several attempts have been carried out to estimate LAI using various types of remote sensing data (Badwhar et al., 1986; Peterson et al., 1987; Turner et al., 1999). It has been primarily based on the empirical relationship between the field-measured LAI and sensor observed spectral responses (Curran et al. 1992 and Peddle et al. 1999). The normalized difference vegetation index (NDVI) has been a popular index with which to estimate LAI across diverse ecosystems. Recent studies have shown that the NDVI may not be very sensitive to values of LAI in particular at the forest ecosystem having the close canopy condition that the LAI value is relatively high (Chen and Cihlar, 1996, Turner et al. 1999).

Spectral characteristics of tea plants are important for monitoring tea plantations by remote sensing. In Sri Lanka an empirical model between NDVI and LAI of tea canopy was developed, relating the LAI of the tea canopy to the spectral reflectance of different types of tea clones for different pruning ages in fifty tea fields (Rajapakse *et. al.,* 2001). Murthy et al. (1995) reported the validity of crop yield models with satellite derived normalized difference vegetation index (NDVI) determined by the strength of association between the two variables. The benefits from using RS and GIS technology depend on the level of success of its application for solving a concrete task. In general, these benefits can be divided into four categories such as scientific, technological, methodological, and economic efficiency (Badarch, 1990).

2. METHODS

2.1 Selection of the region

For this study, the study area chosen was the Sonitpur district of Assam, India. Sonitpur district is spread over an area of 5324 Sq. Kms. on north bank of Brahmaputra River. In terms of area Sonitpur is the second largest district of Assam after Karbi Anglong district.

The District lies between 26° 30’N and 27° 01’N latitude and 92° 16’E and 93° 43’E longitude. Located between mighty Brahmaputra River and Himalayan foothills of Arunachal Pradesh, the district is largely plain with some hills. Brahmaputra River forms the south boundary of the district. A number of rivers which originate in the Himalayan foothills flow southwards and ultimately fall in Brahmaputra River.

According to the 2001 Census, Sonitpur District had a population of 16, 77,874, with a density of 315 persons per Sq. km. In terms of population it ranks third in Assam after Kamrup and Nagaon districts. The people represent a heterogeneous lot. Rather, they are a mosaic of ethnic groups, an admixture of diverse types of people. Sonitpur District falls in the Sub-Tropical climatic region, and enjoys Monsoon type of climate. Summer time is hot and humid, with an average temperature of 29° C. The highest temperature is recorded just prior to the onset of Monsoon (around May-early June). Summer rain is heavy, and is principally caused from late June to early September by the moisture-laden South-West Monsoon, on striking the Himalayan foothills of the north. Such rain is both a boon and a bane for the people. Autumns are dry, and warm. Winters extend from the month of October to February, and are cold and generally dry, with an average temperature of 16° C. Agriculture is the main occupation of the people of Sonitpur district. Tea gardens are next most important feature of economy of the Sonitpur district. There are all together seventy three tea gardens in Sonitpur district. The area covered under these tea gardens is approximately 37554.657ha.

Monabari near Biswanath Chariali is Asia’s largest tea garden. Monabari tea estate comprises an area of 1096 ha with annual tea production of 2.63 10^6 kg in 2000 while Borgang tea estate is the second largest with 1018 ha and an annual production of 1.69 10^6 kg. Most tea gardens were previously owned by European companies like McNeal & Magor, George Williamson Ltd., McLeod Russel, British Assam Tea garden Company$ and Empire Plantation Limited. In recent years, however, many Indian owned companies like Tata Tea and Brooke Bond have taken over the ownership. Apart from the big companies, recently small tea gardens with areas of 5 to 14 ha have emerged in the vicinity of the big tea gardens.

2.2 Data

2.2.1 ASTER: An ASTER (15m) image has been used for monitoring the tea areas. The image has been procured in June, 2004. ASTER products have the following characteristics that are an improvement over past remote sensing products:

- A wide spectral range and a high spectral resolution, covering the spectral range of 0.52 to 11.65 microns with 14 bands.
- 15m, 30m, and 90m spatial resolutions in the visible and near infrared spectral region, the shortwave infrared spectral region, and the thermal infrared spectral region, respectively.
- For band 3 (0.76 - 0.86 microns), both the usual nadir-looking telescope and a backward-looking telescope are used to produce stereoscopic images acquired in the same orbit.

2.2.2 IRS-1C/1D: The LISS III image used in this study was taken on 2 February 2004. It has four bands (red, green, blue and near infra red). The red, green and near infra red bands are of 23.5 m resolution. It has a swath of 127 km for bands 2, 3 and 4 and 134 km for band 5 and NIR. Its repetivity is 25 days.

2.2.3 LANDSAT-7 ETM+ Image: The image was taken on December 2001. It includes spectral regions of VNIR (bands 1-4 with 30 m resolution), SWIR (bands 5 and 7 with 30 m resolution and TIR (band 6, with 60 m resolution) and one panchromatic band 8 with 15 m resolutions. The Enhanced Thematic Mapper Plus (ETM+) is the instrument payload on the LANDSAT-7 spacecraft. The ETM+ is a derivative of the Thematic Mapper (TM) instrument on LANDSAT-4 and LANDSAT-5 (Markham, 2003).

2.2.4 Base Maps: Base maps used in his study include the study area boundaries, latitude and longitude of the area, road maps, contour maps and attribute data collected from toposheets and other sources. Moreover individual garden maps have been collected for each zone at cadastral level. Each garden has its well maintained garden maps with well demarcated sections and their coordinates. These garden maps could be used for identifying the sections undergoing replantation from their section numbers and also the sections showing variations due to soil conditions, environmental factors and cultural practices.

2.3 Methodology

2.3.1 Delineation of diseased tea patches: Remote sensing and GIS technologies have been efficiently used for monitoring several annual crops like rice, wheat, etc. Therefore, developing a similar approach for monitoring tea plantations has become a challenge. The lack of previous studies in monitoring tea using remote sensing provided the idea to develop an approach that can aid in monitoring the growth of plantations and help in taking effective measures when the need arises.

An attempt has been made to assess tea bush health using texture and tonal variations from remotely sensed images. The Gray Level Co-occurrence Matrix (GLCM) technique was applied to categorize the tea patches into healthy, moderately healthy and diseased tea. The diseased patches were delineated using both texture and the classified based images. The study was carried out on the North Bank of Assam, India. LANDSAT, LISS III and ASTER remote sensing images were considered for this study. The LANDSAT image was acquired on December- 2001, the LISS III image on 2nd February 2004 and the ASTER image on June- 2004. Supervised and unsupervised classifications were carried out using the maximum likelihood classifier on all the images. The overall accuracy for all the classified images was then calculated. Texture analysis has been extensively used to classify the remotely sensed images.

2.3.2 Image classification: The basic assumption for image classification is a specific part of the feature space corresponding to a particular class. Classes have to be distinguished in an image and classification needs to have different spectral characteristics. This can be done by comparing spectral reflectance curves. Image classification gives results to certain levels of reliability. The principle of image classification is that a pixel is assigned to a class based on its feature vector by comparing it to predefined clusters in the feature space. Two basic approaches exist for classification: pixel based and object oriented. For this study a pixel based image analysis was used.

- ***Unsupervised Classification:*** Unsupervised classification was carried out for the three images. The spectral classes obtained from the unsupervised classification are based solely on natural groupings in the image values. The spectral classes obtained from all the three images were not initially known. So taking the reference values, the classified data was compared and the spectral classes were identified.
- ***Supervised Classification:*** Here the image analyst supervises the pixel categorization process by specifying, to the computer algorithm, numerical descriptors of various landcover types present in the image. Training samples that describes the typical spectral pattern of land cover classes are defined. Pixels in the image are compared numerically to the training samples and are labeled to landcover classes that have similar characteristics.
- ***Accuracy Assessment:*** In accuracy assessment the main assumption is that the reference data or field data are correct. Classification accuracy will be determined by using three complementary measures which are based on error matrices or confusion matrix derived from independent field data. The two methods used for accuracy assessment are:
- The Error Matrix: Error matrix is a square matrix with the same number of information classes. Numbers in rows are the classification result and numbers in columns are reference data. In the error matrix the elements in the diagonal are pixels that are correctly classified for each information class. The error matrix is the most effective way to represent map accuracy. Accuracy measures like the Overall accuracy (OA), the Producer's accuracy, the User's accuracy (UA) and the Kappa Statistics are well described elsewhere (Congalton), assessing the accuracy of the classified images

In this study, accuracy assessment of MLC based crop/landuse classes was achieved in the form of error matrix by comparing classified output with the ground truth information of independent sites, collected using GPS. A total of 375 sample sites/field was geo-located with GPS for comparison with classified landcover types: healthy tea patches, moderately healthy patches, diseased tea patches, scrubs, river, river bed, barren land and settlements. OA was defined as the percentage of total independent reference pixels that were correctly classified by the MLC. PA was calculated by dividing the number of pixels correctly classified for each class by the total number of independent reference pixels for that class while the user's accuracy was the number of correctly classified pixels divided by the total number of classified pixels for that class.

2.3.3 Texture Analysis: Texture analysis has been extensively used to classify the remotely sensed images. Landuse classification where homogeneous regions with different types of terrains need to be identified is an important application. Haralick *et.al* uses gray level co-occurrence features to analyze the remotely sensed images.

They computed the gray level co-occurrence matrices for a distance of one with four directions (0°, 45°, 90° and 135°). Identifying the perceive qualities of texture in an image is an important first step towards building mathematical models for texture. The intensity variations in an image which characterize texture are generally due to some physical variations in the scene. Texture is usually characterized by the two dimensional variations in the intensities present in the image. Texture is a property of areas and the texture of a point is undefined. Texture involves the spatial distribution of gray levels. Texture in an image can be perceived at different scales or levels of resolution. A region is perceived to have texture when the number of primitive objects in the region is large. Image texture has a number of perceived qualities which plays an important role in describing texture.

Grey Level Co-occurrence Matrix, GLCM (also called the Grey Tone Spatial Dependency Matrix): The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. GLCM texture considers the relation between two pixels at a time, called the **reference** and the **neighbour** pixel. The Grey Level Co-occurrence Matrix (GLCM) has been described in the image processing literature by a number of names including Spatial Grey Level Dependence (SGLD) etc. As the name suggests, the GLCM is constructed from the image by estimating the pair wise statistics of pixel intensity. Each element (i,j) of the matrix represents an estimate of the probability that two pixels with a specified separation having grey levels i and j.

a) Mean: The GLCM mean is not simply the average of all the original pixel values in the image window.

$$\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right) \qquad \mu_j = \sum_{i,j=0}^{N-1} j\left(P_{i,j}\right)$$

The left hand equation calculates the mean based on the reference pixels, μ_i. It is also possible to calculate the mean using the neighbour pixels, μ_j as in the right hand equation. For the symmetrical GLCM, where each pixel in the window is counted once as a reference and once as a neighbour, the two values are identical.

The summation is from 0 to (N-1), not from 1 to N. Since the first cell in the upper left of the GLCM is numbered (0,0), then the i value (0) of this cell is the same as the value of the reference pixel (0). Similarly, the second cell down from the top has an i value of 1, and a reference pixel value of 1. The P_{ij} value is the probability value from the GLCM, i.e. how many times that reference value occurs in a specific combination with a neighbour pixel. It is not a measure of how many times the reference pixel occurs, period, which would be the "regular" mean for the original window. Multiplying i by P_{ij} effectively divides the entry i by the sum of entries in the GLCM, which is the number of combinations in the original window. This is the same as is done when calculating a mean in the "usual" way.

b) Variance: Variance in texture calculates the dispersion of GLCM values around their mean,. As GLCM variance uses GLCM values it deals specifically with the combinations of reference and neighbour pixel. In that sense it differs from the variance of grey levels in the original image. Variance (v) calculated using the gray levels i or j gives the same result, since the GLCM is symmetrical.

$$v_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-\mu_i\right)^2 \quad v_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(j-\mu_j\right)^2$$

$$v_i = \sqrt{v_i^2} \qquad v_j = \sqrt{v_j^2}$$

c) Contrast: Contrast is also called sum of squares variance. This measures the amount of local variation in the image and is the opposite of homogeneity.

$$Contrast = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-j\right)^2$$

When i and j are equal, the cell is on the diagonal and (i-j) = 0. These values represent pixels entirely similar to their neighbour, so they are given a weight of 0. If i and j differ by 1, there is a small similarity, and the weight is 1. If i and j differ by 2, contrast is increasing and the weight is 4. The weights continue to increase exponentially as (i-j) increases.

d) Homogeneity: Homogeneity weights values by the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal.

$$Homogenity = \sum_{i,j=0}^{N} \left(P_{i,j} \big/ 1+\left(i-j\right)^2 \right)$$

e) Dissimilarity: Instead of weights increasing exponentially (0, 1, 4, 9, etc.) as we move away from the diagonal, the dissimilarity weights increases linearly (0, 1, 2, 3 etc.).

$$Dissimilarity = \sum_{i,j=0}^{N} P_{i,j} \left| i-j \right|$$

f) Entropy: The concept comes from thermodynamics. It refers to the quantity of energy that is permanently lost to heat ("chaos") every time a reaction or a physical transformation occurs. Entropy cannot be recovered to do useful work. Because of this, the term is used in non technical speech to mean irremediable chaos or disorder. Also, as with ASM, the equation used to calculate physical entropy is very similar to the one used for the texture measure. Energy is, in this context, the opposite of entropy. Energy can be used to do useful work. In that sense it represents orderliness. This is why "Energy" is used for the texture that measures order in the image.

$$E = \sum_{i,j=0}^{N-1} P_{i,j}\left[-\ln P_{i,j}\right]$$

The term P * ln(P) is maximized where its derivative with respect to. P is 0. By the product rule, this derivative is P * d(ln(P))/d(P) + d(P)/d(P) * ln(P) which simplifies to 1 + ln(P) = 0, yielding P = 1/e. This means that the maximum of the term to be summed occurs when P is 1/e, which is about 0.378. However by definition the sum of Pij = 1. With this constraint, the overall maximum of the sum (i.e. of ENT) is 0.5. This maximum is reached when all probabilities are equal. Conceptually this makes sense because when all probabilities of DN pairs are equal, we have a random distribution of DN values, which would yield maximum "chaos" or entropy.

g) Angular Second Moment (ASM): This measures homogeneity of the image. It is specified by the matrix of relative frequencies *P*(*i*,*j*) with which two neighbouring pixels occur on the image, one with grey value i and the other with grey value j.

$$ASM = \sum_{i,j=0}^{N-1} P_{i,j}^{\ 2} \text{ for any particular direction}$$

The square root of the ASM is sometimes used as a texture measure, and is called **Energy**.

$$Energy = \sqrt{ASM}$$

h) Correlation: The Correlation texture measures the linear dependency of grey levels on those of neighbouring pixels. GLCM Correlation can be calculated for successively larger window sizes. The window size at which the GLCM Correlation value declines suddenly may be taken as one definition of the size of definable objects within an image. GLCM Correlation is quite a different calculation from the other texture measures described above. As a result, it is independent of them (gives different information) and can often be used profitably in combination with another texture measure. It also has a more intuitive meaning to the actual calculated values: 0 is uncorrelated, 1 is perfectly correlated.

$$Correlation = \sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\delta_i^2)(\delta_j^2)}}\right]$$

The GLCM variance is zero when the area is uniform. In a normalized GLCM, a uniform image area has a single entry of 1 in the diagonal corresponding to the row and column headed by the original GL value in the pixels of the image. The mean then becomes $\mu = i = j$. When calculating the GLCM variance, $P_{ij} = 0$ for every value except the single entry of 1. The formula collapses to $= 1(i - \mu)^{2,}$ but since $\mu = i$, this becomes $1 (i=i)^2 = 0$.

In this study, we use the Grey Level Co-occurrence Matrix (GLCM) method for studying the texture of the tea areas to enable us to distinguish between healthy and affected tea patches. The GLCM technique was applied to all the images and the different parameters were studied. After generating the images they are compared with maps showing disease patterns to see whether the affects observed on those could be observed on the texture images.

2.4 Results and Discussions

2.4.1 Delineation of diseased tea patches: Tea garden patches were masked from the landuse/landcover maps and the disease patches were delineated. From the images the gradual spread of the diseases at three different dates could be well observed.

The spread was observed between 2001 and 2004. The LANDSAT image showed healthy, moderately affected and affected patches; these, however, could not be observed in the LISS III and ASTER image. Comparing the Landsat, LISS III and the ASTER images at three different dates, we notice that the affected patches visible at the LANDSAT image have changed to moderately affected at the LISS III image, moderately affected patches to affected patches and the diseased patches to healthy patches in LISS III. Similarly, comparing ASTER image with LISS III we observed that the moderately affected patches in LISS III changed to healthy patches and healthy patches to diseased patches in ASTER. This shows how the disease spread between February and June in 2004. Moreover a stronger infestation was found during June 2004 as there were heavy rains accompanied by high temperature and high relative humidity during that period.

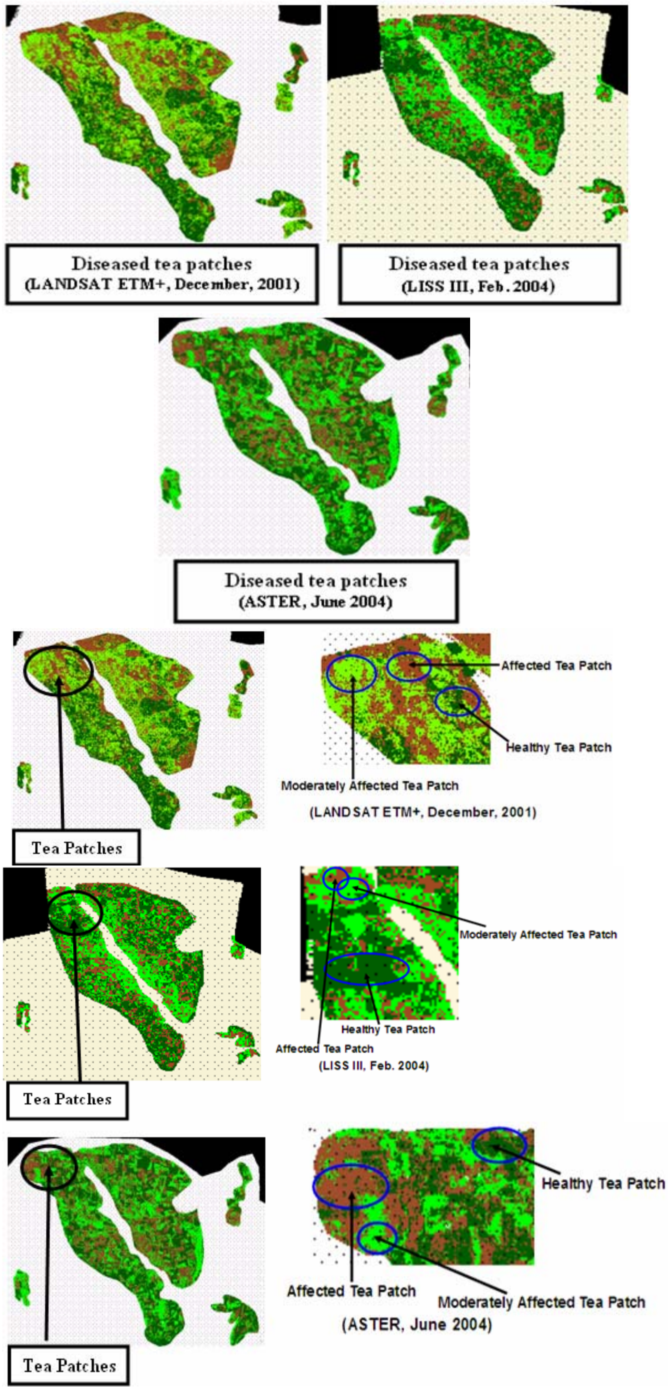

Figure 3. Images showing the gradual spread of the diseases at different time periods

Creating a texture image: The result of a texture calculation is a single number representing the entire window. This number is put in the place of the centre pixel of the window, then the window is moved one pixel and the process is repeated of calculating a new GLCM and a new texture measure. In this way an entire image is built up of texture values. Each cell in a window must sit over an occupied image cell. This means that the centre pixel of the window cannot be an edge pixel of the image. If a window has dimension N x N, a strip (N-1)/2 pixels wide around the image will remain unoccupied. The usual way of handling this is to fill in these edge pixels with the nearest texture calculation.

Further delineation of disease tea patches was tried using the texture based classification in all the three dataset. Texture analysis for LANDSAT, LISS III and ASTER images were carried out using various windows like 3 × 3, 5 × 5, 7 × 7, 9 × 9, 11 × 11, 13 × 13, 15 × 15, 17 × 17 and 19 × 19 and with band wise generated texture images. It was found that only the 3 × 3 window yielded good texture results. The other windows gave hazy and blurred texture images from which the tea patches could not be identified and image analysis could not be done. The band giving the best texture result in a 3 × 3 window was then selected for analysis purposes.

For the **LANDSAT** image, Band 4 (NIR) and 5 (IR) gave good texture results. From the mean results, the tea patches could be well identified. The other parameters showed large interclass mixing. From the mean results the healthy, moderately healthy and diseased patches could be separated, but mixing still occurred among other landuse classes.

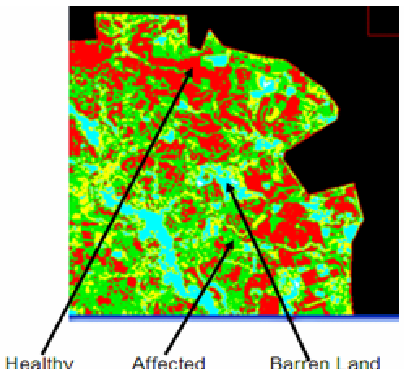

Figure 4. LANDSAT Image showing the healthy and affected patches obtained from texture based analysis.

Band 3 (NIR) and Band 4 (MIR) gave good texture results for **LISS III**, with the tea patches prominently identifiable from the mean results. The texture images of LISS III were further analyzed to identify between the healthy, moderately healthy and diseased tea patches.

Here moderately healthy and diseased tea could not be separated. Therefore, the analysis could be done only for healthy and affected patches (both moderately affected and diseased patches combined).

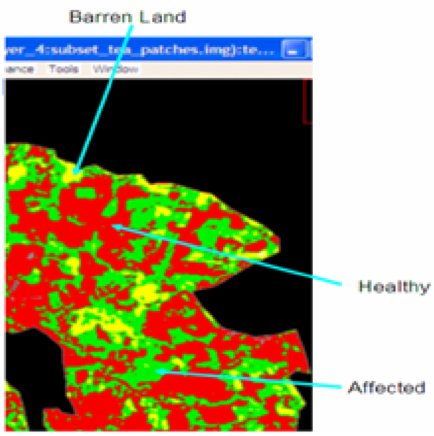

Figure 5. LISS III Images showing the healthy and affected patches obtained from texture based analysis.

All three bands gave good texture results for the **ASTER** image, allowing the three patches could to be clearly observed. Healthy, moderately healthy and affected tea patches could be distinguished within the ASTER image.

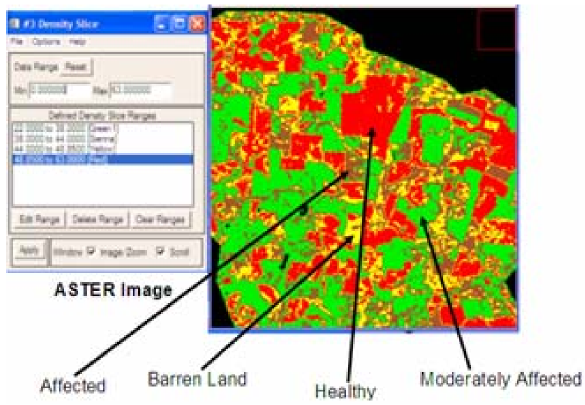

Figure 6. ASTER Images showing the healthy, moderately healthy and affected tea patches obtained from texture based analysis.

ASTER, being a high resolution image, provides good texture results as compared to LANDSAT and LISS III images. LANDSAT and LISS III images showed large interclass mixing as compared to ASTER images.

From this we conclude that, for this type of study, the texture analysis should be carried out using high resolution images like LISS IV or IKONOS. The other parameters of texture were also tested but none of them could produce good results due to excessive interclass mixing.

2.4.2 A Qualitative Evaluation of the Percentage of Healthy, Moderately Healthy and Diseased Tea Areas: The tea patches were masked out from the landuse/landcover maps for further analysis to find the percentage of healthy, moderately healthy and diseased tea patches. The formula used for estimating the percentage of affected and non-affected tea is given below:

Healthy Tea Patches (%) = *Area of Healthy Tea Patch / Total Tea Area*

Moderately Affected Tea Patches (%) = *Area of Moderately Healthy Tea / Total Tea Area*

Diseased Tea Patches (%) = *Area of Diseased Tea / Total Tea area*

Classes	LANDSAT Image		LISS III Image		ASTER Image	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Healthy Tea Patches	26737	60	17759	44	6209.9	24.9
Moderately Healthy Tea Patches	10426	24	14878	37	12496	50.1
Diseased Tea Patches	7158	16.2	7801	19.3	6260	25.1
Grand Total	44321		40438		24965.9	

Table 1. Table showing the percentage of affected and non-affected tea patches

Using the LANDSAT, LISS III and ASTER landuse/landcover images, the area for the individual classes were computed (in ha). Among the classes, the area of healthy, moderately affected and diseased tea patches were taken into consideration from which the percentage of healthy, moderately healthy and diseased tea patches. From the table, the variations in tea plantations at three different dates were observed. The LANDSAT image of December, 2001 showed 60.4% area under healthy tea, 23.6% area under moderately affected tea and 16.2% area under diseased tea. For the LISS III image of February, 2004, it was found that 43.9% area under healthy tea, 36.8% area under moderately affected tea and 19.3% area under diseased tea. Similarly for ASTER image of June, 2004, area under healthy tea was found to be 24.9%, moderately healthy tea was found to be 50.1% and diseased tea to be 25.1%. Clearly, the disease was most prominent in June. From June to October, the weather remained hot and humid accompanied by heavy monsoon showers. This is the peak period for the outbreak of **Red Spider Mite** attack and the **Helopeltis** attack. The tea bushes are highly prone to these two diseases during this period and once the disease breaks out it spreads rapidly.

2.4.3 Detection of Affected Plantations from Remotely Sensed Images: We were able to identify and detect the affected and non-affected tea patches from remotely sensed images. The disease started in the year 1999 but was not severe at the initial stage. During the year 2000 and 2001, there was heavy monsoon showers accompanied by high temperature and humidity. These conditions have favoured the spread of the disease. Between 2003 and 2005 the spread was quite severe. When the LANDSAT ETM+ (December, 2001), LISS III (February, 2004) and ASTER (June, 2004) images were compared, it was observed that there was a gradual spread of the disease from one place to another. The spread was minutely observed in all the images. It was further verified on the field. All affected tea patches from 1999 to 2005 were identified from the garden records and from the field visit. Field records showed that there was a gradual spread of the disease in the gardens. All the spots were visited and marked in the images and compared. From this it was quite clear that whatever has been visually interpreted from the image was correct and the spread of the disease could be well established.

3. CONCLUSIONS AND DISCUSSION

We conclude that texture analysis is useful for studying tea bush health at tea plantations. We could distinguish healthy, moderately healthy or diseased bushes. The Gray Level Co-occurrence Matrix (GLCM) techniques have been able to delineate affected from non-affected tea patches. A qualitative assessment was conducted to assess the percentage area with affected and that with non-affected tea plants. The LANDSAT Image showed 60% area under healthy, 24% under moderately healthy and 16.2% under diseased tea patches. The LISS III Image showed 44% area under healthy, 37% under moderately healthy and 19.3% area under diseased tea patches. Similarly, the ASTER Images showed 24.9% area under healthy, 50.1% under moderately healthy and 25.1% area under diseased tea patches.

From this study it has been observed that ASTER image could delineate the pest and diseased infested areas into healthy, moderately healthy and diseased / pests tea areas without any interclass mixing which was well observed in the LANDSAT and LISS III images.

A decision on identifying the best texture analysis technique could be judged only when applying available texture techniques to a similar study, like the current one, and then comparing their results. In addition, such an analysis should be carried out in high resolution images like an IKONOS image or a LISS IV image.

Further research should be carried out with different sensors of various spatial, spectral and temporal resolutions to do a comparative assessment or analysis. Different texture analysis techniques should be used and the results should be compared with other techniques to find the best suitable technique. Knowledge and object based classification should be further explored so that the results can be compared with the texture based classification.

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