RESEARCH ARTICLE

MAPPING SUGARCANE YELLOW LEAF DISEASE AFFECTED AREA USING REMOTE SENSING TECHNIQUE

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Abstract

Remote sensing provides information on coverage, mapping and classification of land-cover features, such as vegetation, soil, water and forests. Satellite imageries are being used to map areas under different crops and cultivars, and to identify areas with specific characteristics like deficiency symptoms, pest and disease infestation, etc., using the spectral reflectance at canopy and pixel scales. In an attempt to identify and map sugarcane fields affected by the Yellow Leaf Disease (YLD), sugarcane growing fields in the Bhavani command areas of Erode district of Tamil Nadu State, India, were surveyed. The digital satellite imagery of IRS P6, Path 100 and Row 65 which covers the surveyed area was obtained from National Remote Sensing Center (NRSC), Hyderabad, India, and the sugarcane fields with and without YLD were demarcated. The Digital Number (DN) values were extracted using the customized programme developed in C# language of Visual Studio 2008 in the dot net platform. The DN values in the YLD affected fields were lower than the YLD free field in all the four bands. The DN values for the four bands were analyzed using the bootstrap confidence intervals. The differences in DN values were compared using the difference of mean (d_{AVE}) which is one of the measures of difference used in unpaired data, where no dependence is assumed between the two groups of data. A confidence interval for d_{AVE} provides quantitative information, which also includes a statistical test (by looking whether it contains zero) but is not restricted to it. The healthy sugarcane field gave significantly higher DN values than YLD affected fields. The DN values in the healthy sugarcane field were higher by 7.5 units with 95% BCa confidence interval (1, 30 DN values) when compared to YLD affected fields. The results reveal the possibility of developing a subpixel classification model to the highest classification accuracies for demarcating the YLD affected sugarcane fields.

Key Words: Sugarcane, yellow leaf disease, YLD, remote sensing

Introduction

Sugarcane is one of the largest field crops cultivated in more than 90 countries with a worldwide cane production of 1.69 billion tonnes (http://faostat.fao.org).Yellow Leaf Disease (YLD) of sugarcane is reported as an emerging threat to sugarcane cultivators in many countries. The symptoms of infection usually appear during 6-8 months age in the field. Intense yellowing of midribs on the abaxial surface, lateral spread of yellow discolouration on the leaf lamina followed by tissue necrosis from the leaf tip spreading downwards along the midrib and a bushy appearance of the top of the plant due to internode shortening in maturing plants are the common symptoms recorded in different countries (Viswanathan et al. 2009). In Venezuela, 60% of yield losses was reported due to YLD (Izaquirre-Mayoral et al. 2002) and in Hawaii 20-30% yield loss wasreported. It has been

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established that the disease severity increases in the ratoon and subsequently yield reductions are comparatively higher in ratoon than the plant crop.

Crop monitoring is one of the most studied applications in Precision Farming systems. It considers data and information from observations carried out directly on the crop, such as phenological, nutritional, and phytosanitary status. Crop monitoring is done to maximize the production in quantity and quality (Lamb and Bramley 2001; Arnó et al. 2009). Early diagnosis of vegetation stress, which includes a variety of production limiting factors, is of growing importance in the framework of Precision Agriculture (PA), especially with regards to integrated pest management. In fact, health monitoring in crops is critical for sustainable agriculture. Early information on crop health and disease detection isused: (i) to facilitate the control of disease through proper management strategies, (ii) to allow more efficient application of agrochemicals and (iii) to improve productivity (Sankaran et al. 2010). This is especially important for capital-intensive industrial crops like sugarcane.

Remote sensing provides information on coverage, mapping and classification of land-cover features, such as vegetation, soil, water and forests. Satellite imageries are being used to map area under different crops, cultivars and also to identify areas with specific characteristics like deficiency symptoms, pest and disease infestation, etc. using the spectral reflectance at canopy and pixel scales. Palaniswami et al. (2006) had successfully utilized the spectral mixture analysis for subpixel classification of coconut land cover mapping using satellite imagery. Spectral information in satellite imageries reflects agronomic variables and can be used for crop monitoring and yield forecasting in sugarcane (Simo˜es et al. 2005). Remote Sensing provides an alternative method for rapid determination ofsugarcane yellow leaf virus (SCYLV) impacted populations. Diseases and other stresses were found to affect the amount and quality of electromagnetic radiation reflected from leaves of plants, and difference in reflectance can, therefore, be used to detect pathogen infections (Guan and Nutter 2002; West et al. 2003). To demonstrate the possibility of applying remote sensing technique to map the YLD affected sugarcane areas, this study was undertaken using the difference ofmeans between DN values of YLD affected field and healthy field abbreviated as $d_{AVE.}$A confidence interval for d_{AVE} provides quantitative information, which also includes a statistical test (by looking whether it contains zero) but is not restricted to it as given by Mudelsee and Alkio (2007) to separate the healthy and YLD affected sugarcane fields.

Material and methods

Sugarcane farms in Bhavani command areas of Erode district of Tamil Nadu State, India, were surveyed for YLD. The digital satellite imagery of IRS P6, Path 100 and Row 65 was obtained from National Remote Sensing Center (NRSC), Hyderabad, India, and sugarcane fields with and without YLD were demarcated. The Digital Number (DN) values were extracted using the customized programme developed in C# language of Visual Studio 2008 in the dot net platform.

Statistical analysis

The DN values for the four bands were analyzed using the bootstrap confidence intervals proposed by Mudelsee and Alkio (2007). A brief description of the method is given below:

The DN values of healthy and YLD affected fields were compared using the difference of mean (d_{AVE}). The mentioned measures of difference were used in unpaired experiments, where no dependence is assumed between the two treatment groups. A confidence interval for d_{AVE} provides quantitative information, which also includes a statistical test (by looking whether it contains zero) but is not restricted to it.

$\hat{d}_{AVE}$=AVE(x)-AVE(y)

where

$\{x(i), i=1,\ldots,n_x\}$, $\{y(i), i=1,\ldots,n_y\}$ are the treatments x and y data

AVE(x) is sample median of x and AVE(y) is sample median of y

The bootstrap (Efron and Tibshirani 1993) is the prime source of confidence intervals for the variables measuring differences between the two treatment groups. The nonparametric bootstrap (Efron 1979) was used to estimate standard errors of the difference measures. In case of an unpaired experiment, draw with replacement of a bootstrap sample of same size $\{x^*(i), i=1,\ldots,n_x\}$, $\{y^*(i), i=1,\ldots,n_y\}$ from the treatment data set under comparison was followed.

The bootstrap replication of a difference measure from the bootstrap samples was calculated as $\hat{d}_{AVE}$ =AVE(x*)-AVE(y*) where AVE(x*) is the sample mean of x*. The procedure was repeated by resampling and calculating until B bootstrap replications existed for $\hat{d}_{AVE}$. The bootstrap estimate of standard error, $\hat{se}$, was calculated as the sample standard deviation of the bootstrap replications.

$$\hat{se}(\hat{d}_{AVE}) = \left\{\sum_{b=1}^{B}\left(\hat{d}^{*b}_{AVE} - \langle \hat{d}^{*}_{AVE} \rangle\right)^2 \Big/ (B-1)\right\}^{1/2}$$

where $\langle \hat{d}^{*}_{AVE} \rangle = \sum_{b=1}^{B} \hat{d}^{*b}_{AVE} / B$ and $\hat{d}^{*b}_{AVE}$ denotes the b[th] bootstrap replication of $\hat{d}_{AVE}$

The bootstrap bias-corrected and accelerated (BCa) confidence interval, in the case of $\hat{d}_{AVE}$, is

$$\left[\hat{d}^{*(\alpha 1)}_{AVE},\ \hat{d}^{*(\alpha 2)}_{AVE}\right]$$

$$\alpha 1 = \Phi\left[\hat{z}_0 + \frac{\hat{z}_0 + z^{(\alpha)}}{1 - \hat{a}\{\hat{z}_0 + z^{(\alpha)}\}}\right]$$

$$\alpha 2 = \Phi\left[\hat{z}_0 + \frac{\hat{z}_0 + z^{(1-\alpha)}}{1 - \hat{a}\{\hat{z}_0 + z^{(1-\alpha)}\}}\right]$$

Bias correction, $\hat{z}_0$, is computed as

$$\hat{z}_0 = \Phi^{-1}\left(\frac{\text{number of replications where } \hat{d}^{*b}_{AVE} < \hat{d}_{AVE}}{B}\right)$$

Acceleration, $\hat{a}$, the two–sample recipe provided by Mudelsee and Alkio (2007), was computed as

$$\hat{a} = \frac{\sum_{i=1}^{n_x}\sum_{j=1}^{n_y}\left\{\langle \hat{d}_{AVE(i,j)} \rangle - \hat{d}_{AVE(i,j)}\right\}^3}{6\left[\sum_{i=1}^{n_x}\sum_{j=1}^{n_y}\left\{\langle \hat{d}_{AVE(i,j)} \rangle - \hat{d}_{AVE(i,j)}\right\}^2\right]^{3/2}}$$

where $\hat{d}_{AVE(i,j)}$ is the jackknife value of $\hat{d}_{AVE}$.

That is, let x(i)denote the original treatment sample with point x(i) removedand y(j) the control sample without y(j), then $\hat{d}_{MED(i,j)}$ =AVE{$x_{(i)}$}- AVE{$y_{(j}$} where AVE{$x_{(i)}$} is the sample median calculated without point x(i). The median, $\langle \hat{d}_{AVE(i,j)} \rangle$, is given by $\left\{\sum_{i=1}^{n_x}\sum_{j=1}^{n_y}\hat{d}_{AVE(i,j)}\right\} \Big/ (n_x n_y)$

$z^{(\alpha)}$ - is the á quantile of standard normal distribution

Φ is the cumulative standard normal distribution function

Φ^{-1} is the inverse of the standard normal function

The differences in DN values were compared using the difference of mean (d_{AVE}). The difference of mean (d_{AVE}) is one of the measures of difference used in unpaired data, where no dependence is assumed between the two groups of data. A confidence interval for d_{AVE} provides quantitative information, which also includes a statistical test (by looking whether it contains zero) but is not restricted to it.

Results and discussion

Of late, the most widely used mechanism for monitoring stress in crops is scouting, though an expensive, labour-intensive and time consuming process. Current developments in agricultural technology have led to a growing demand for a new era of automated non-destructive methods of plant disease detection. Spectroscopic and imaging techniques are unique disease monitoring methods that have been used to detect diseases and stress caused by different factors in plants.

The results of the current study revealed that the DN valuesof YLD affected fields were lower than those of YLD free field in all the four bands (Fig. 1). Healthy sugarcane field shad significantly higher DN values than YLD affected fields.Various studies have been conducted regarding the identification of biotic and abiotic plant stresses such as herbicide application (Smith et al. 2005), fungal infection (Zhang et al. 2005), water stress (Kriston-Vizi et al. 2008) and nutrient deficiency (Zhao et al. 2005). Studies were conducted with various crops to distinguish diseased leaves from healthy leaves (Blanchfield et al. 2006; Moshou et al. 2006; Huang et al. 2007; Lins et al. 2009). Many diseases are known to cause changes in leaf pigments, biochemical components and metabolic alterations in infected leaves (Lehrer et al. 2007). These

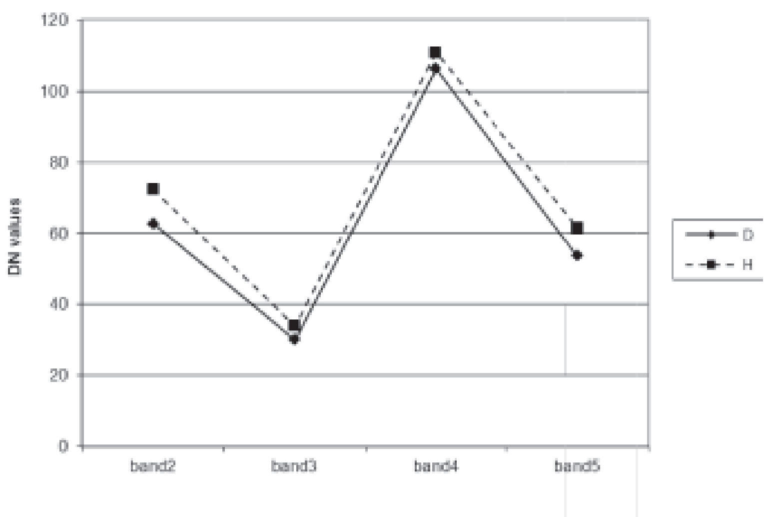

Fig.1. DN values of healthy and YLD infected sugarcane fields in different spectral bands (D- YLD affected sugarcane field and H - YLD free sugarcane field; Band 2 [Green] - 0.52 to 0.59 microns, Band 3 [Red]- 0.62 to 0.68 microns, Band 4 [NIR] - 0.76 to 0.86 microns and Band 5 [NIR]- 1.55 - 1.70 microns

pathological conditions of plants can influence spectral characteristics of leaf tissue that can be detected in the visible and/or the near infrared (NIR) regions of the electromagnetic spectrum. In fact, the visible and infrared regions are known to provide the maximum information on the physiological stress levels in plants (Xu et al. 2007). Thus, the different spectral reflectance between healthy and infected leaves can be used to identify a plant's health status. Such changes in reflectance characteristics have been used to diagnose disease symptoms in plants. Delalieux et al. (2007) investigated the capability of hyperspectral analysis for early white apple scab (*Venturia inaequalis*) detection and to develop an approach to explore this potential.

The differences in DN values were compared using the difference of mean (d_{AVE}). The DN values in the healthy sugarcane field were higher by 7.5 units with 95% BCa confidence interval (1, 30 DN values) when compared to YLD affected fields. The results reveal the possibility of developing a subpixel classification model to the highest classification accuracies for demarcating the YLD affected sugarcane fields.

In general, this approach can be applied to compare two groups using bootstrap confidence interval DN values and to classify satellite images digitally. This approach was successfully applied in several studies. Goyal and Sidharta (2004) compared the measured and modeled distributions of suspended particulate matter in an area around a thermal power station in India. The demonstration of non-significant differences offered credence to their modeling effort. The effects of implementation of different environmental models was quantified by Giannakopoulos et al. (2004) using a chemical transport model with/without a scheme of mixing processes in the planetary boundary layer (PBL) to study the global ozone distributions. The PBL scheme had a significant influence, which was quantified using bootstrap confidence intervals. Peel et al. (2005) found that the selection of biophysical parameters for eucalypts had negligible influence on the simulation of the January climate of Australia. Such a conclusion was strengthened by evaluating the differences using bootstrap confidence intervals. For realtime monitoring systems, a software using a ''bootstrap tool'' in data analysis for low-resolution image analysis was developed by Chrysoulakis et al. (2005). The software was used to detect the occurrence of major industrial accidents using satellite imagery data. Quinn et al. (2005) designed a system for real-time management of dissolved oxygen in a ship channel in California, using data analysis with bootstrap confidence intervals.

The method presented here for quantifying the differences in DN values of satellite image data to map YLD affected sugarcane fields demonstrates the possibility of developing subpixel classification model to the highest classification accuracies for demarcating the YLD affected sugarcane fields. It avoids cumbersome image transformations and is robust with respect to the distributional shape.

References

Arnó J, Martinez-Casasnovas JA, Ribes-Dasi M, Rosell JR (2009) Review: Precision viticulture. Research topics, challenges and opportunities in site-specific vineyard management. Spanish J Agric Res 7(4):779-790.

Blanchfield AL, Robinson SA, Renzullo LJ, Powell KS (2006) Phylloxera-infested grapevines have reduced chlorophyll and increased photoprotective pigment content-can leaf pigment composition aid pest detection? Functional Plant Biol 33(5):507-514.

Chrysoulakis N, Adaktylou N, Cartalis C (2005) Detecting and monitoring plumes caused by major industrial accidents with JPLUME, a new software tool for low-resolution image analysis. Environmental Modelling and Software 20:1486-1494.

Delalieux S, Van Aardt J, Keulemans W, Schrevens E, Coppin P (2007) Detection of biotic stress (*Venturia inaequalis*) in apple trees using hyperspectral data: non-parametric statistical approaches and physiological implications. European Journal of Agronomy 27(8):130-143.

Efron B (1979) Bootstrap methods another look at the jackknife. Annals of Statistics 7:1-26.

Efron B, Tibshirani RJ (1993) An introduction to the bootstrap. 1st Edn., Chapman and Hall, Inc., New York, 0-412-04231-2.

Giannakopoulos C, Chipperfield MP, Law KS, Shallcross DE, Wang KY, Petrakis M (2004) Modelling the effects of mixing processes onthe composition of the free troposphere using a three-dimensional chemical transport model. Environmental Modelling and Software 19: 391-399.

Goyal P, Sidharta (2004) Modeling and monitoring of suspended particulate matter from Badarpur thermal power station, Delhi. Environmental Modelling and Software 19:383-390.

Guan J, Nutter Jr FW (2002) Relationships between defoliation, leaf area index, canopy reflectance, and forage yield in the alfalfa-leaf spot pathosystem. Computers and Electronics in Agriculture 37(1-3):97–112.

Huang W, Lamb DW, Niu Z, Zhang Y, Liu L, Wang J (2007) Identification of yellow rust in wheat using in situ spectral reflectance measurements and airborne hyperspectral imaging. Precision Agric 8(4-5):187-197.

Izaguirre-Mayoral ML, Carballo O, Alceste C, Romano M, Nass HA (2002) Physiological performance of asymptomatic and yellow leaf syndrome-affected sugarcanes in Venezuela. J Phytopathol 150:13-19.

Kriston-Vizi J, Umeda M, Miyamoto K (2008) Assessment of the water status of mandarin and peach canopies using visible multispectral imagery. Biosystem Engineering 100(3):338-345.

Lamb DW, Bramley RGV (2001) Managing and monitoring spatial variability in vineyard productivity. Australian J Grape Wine 449a:889-892.

Lehrer AT, Moore PH, Komor E (2007) Impact of sugarcane yellow leaf virus (SCYLV) on the carbohydrate status of sugarcane: comparison of virus-free plants with symptomatic and asymptomatic virus-infected plants. Physiol Mol Plant Pathol 70(4-6):180-188.

Lins EC, Belasque Jr J, Marcassa LG (2009) Detection of citrus canker in citrus plants using laser induced fluorescence spectroscopy. Precision Agric 10(4):319-330.

Moshou D, Bravo C, Wahlen S, West J, McCartney A, De Baerdemaeker J, Ramon H (2006) Simultaneous identification of plant stresses and diseases in arable crops using proximal optical sensing and self-organising maps. Precision Agriculture 7(3):149-164.

Mudelsee M, Alkio M (2007) Quantifying effects in two-sample environmental experiments using bootstrap confidence intervals. Environmental Modelling and Software 22:84-96.

Palaniswami C, Upadhyay AK, Maheswarappa HP (2006) Spectral mixture analysis for subpixel classification of coconut. Curr Sci 91:1706-1711.

Peel DR, Pitman AJ, Hughes LA, Narisma GT, Pielke Sr RA (2005) The impact of realistic biophysical parameters for eucalypts on the simulationof the January climate of Australia. Environmental Modelling and Software 20: 595-612.

Quinn NWT, Jacobs K, Chen CW, Stringfellow WT (2005) Elements of a decision support system for real-time management of dissolved oxygen in the San Joaquin River Deep Water Ship Channel. Environmental Modelling and Software 20: 1495-1504.

Sankaran S, Mishra A, Ehsani R, Davis C (2010). A review of advanced techniques for detecting plant disease. Computers and Electronics in Agriculture 72(1):1-13.

Simo˜es MS, Rocha JV, Lamparelli RAC (2005) Spectral variables, growth analysis and yield of sugarcane. Scientia Agricola (Piracicaba, Brazil) 62(3):199–207.

Smith KL, Steven MD, Colls JJ (2005) Plant spectral response to gas leaks and other stresses. Intern J Remote Sensing 26(18):4067-4081.

Viswanathan R, Karuppaiah R, Malathi P, Ganesh Kumar V, Chinnaraja C (2009) Diagnosis of *sugarcane yellow leaf virus* in asymptomatic sugarcane by RT-PCR. Sugar Tech 11:368-372.

West JS, Bravo C, Oberti R, Lemaire D, Moshou D, McCartney HA (2003) The potential of optical canopy measurements for targeted control of field crop diseases. Annu Rev Phytopathol 41:593-614.

Xu HR, Ying YB, Fu XP, Zhu SP (2007) Near-infrared spectroscopy in detecting leaf miner damage on tomato leaf. Biosystems Engineering 96(4):447-454.

Zhang M, Qin Z, Liu X (2005) Remote sensed spectral imagery to detect late blight in field tomatoes. Precision Agriculture 6(6):489-508.

Zhao D, Reddy KR, Kakani VG, Reddy VR (2005) Nitrogen deficiency effects on plant growth; leaf photosynthesis and hyperspectral reflectance properties of sorghum. European J Agron 22(4):391-403.