Research & Analysis Journals

Available online at www.rajournals.in

RA JOURNAL OF APPLIED RESEARCH

ISSN: 2394-6709

DOI:10.33826/rajar/v6i6.01

Volume: 06 Issue: 06 June-2020

International Open Access

Impact Factor- 6.595

Page no.- 2694-2697

Remote Sensing Parameters Role in Agriculture: A Review

Manjeet[1], Anurag[2], Ram Niwas[3]

[1,2,3]Department Of Agricultural Meteorology, Ccs Haryana Agricultural University, Hisar

ARTICLE INFO

Published Online: 30 June 2020

ABSTRACT

Vegetation Indices (VIs) obtained from remote sensing (RS) based canopies are quite simple and effective algorithms for quantitative and qualitative evaluations of vegetation cover, vigor, and growth dynamics, among other applications. These indices have been widely implemented within RS application using different airborne and satellite platforms with recent advances using Unmanned Aerial Vehicles (UAV). Vegetation indices (VIs) are different combination of surface reflectance at two or more wavelength designed to highlight a particular property of vegetation. Crop yield estimates at regional scale are essential for proper planning and policy making in the agriculture sector of the country. Remotely sensed images are provided great potential in crop growth and yield over large area owing to their spatial and temporal coverage. Over the last few decades, the most commonly used yield-vegetation index has been criticized because of its strong experiential character. To predict of wheat yield using normalized difference vegetation index (NDVI) and different weather parameter during different phases of crop growth. To improve crop production and prediction depend upon the crops factors such as crop genotype, soil characteristics, agronomic practices, weather condition and biotic stresses that can be identify by remote sensing indices at instant time. The present study introduces the spectral characteristics of vegetation and application in crop production and status of crop growth at course of growth. . To improve crop production and prediction depend on remote sensing indices sensitive to spectral reflectance of crop at instant time.

Corresponding Author: **Manjeet**

KEYWORDS: Remote sensing, Normalized Difference Vegetation Indices, Hyper-spectral

INTRODUCTION

Remote sensing sensor capture reflectance of plant health, to monitor plant changes over the course of a growing season (Richardson *et al*., 2004).Remote sensing help to assessing crop condition based on satellite and ground images. Remote sensing techniques for detection of crop stress due to pests and diseases is based on the assumption that stresses induced by them interfere with photosynthesis and physical structure of the plant, affect absorption of light energy and thus alter the reflectance spectrum of plants (Ray S.S *et al.*,1999). Leaf chlorophyll content is an important variable for agricultural remote sensing because of its close relationship to leaf nitrogen content (Hunt *et al.,* 2013). Mapping vegetation water status with remote sensing provides useful information to monitor plant drought stress. The timely and accurate estimation of grain yield and annual fluctuation can help governments to plan effective strategies (Ren *et al*., 2008). From space agricultural monitoring to pre-harvest assessment crop yield and production has been a topic of research since the early 1970s (Wall *et al.,* 2007). This model integrates agronomic parameters and meteorological factors, which offer unique advantages in predicting crop yield in large-scale monitoring (Jiao *et al.*, 2005*;* Wang *et al.*,2012). Spectral reflectance is a new, real time and non-destructive Hyperspectral remote sensing application to monitor plant water status and physiological changes. The spectral reflectance responses induced by water stress reflect the interaction and coupling of carbon, nitrogen and water cycle (L. Chang and Liu 2016).

Normalized Difference Vegetation Index (NDVI):

Reflectance difference in the visible and NIR regions have led to the development of spectral vegetation indices. Spectral vegetation indices are mathematical transformation of reflectance values at different parts of the spectrum, intended to normalize the measurement made in varied environmental conditions (Riedell and Blackmer, 1999).

Normalized Difference Vegetation Index (NDVI) is the normalized difference of reflectance in NIR and Red bands (Rouse *et al.* 1974)

$$NDVI= (R_{NIR}-R_{RED}) / (R_{NIR}+R_{RED})$$

Ratio Vegetation Index (RVI) is the ratio of the reflectance in NIR and red band. They were used to detect plant stress and can be saturated at high leaf area index (LAI) (Ranjitha *et al.* 2014).

Spectral Response of Vegetation:

Green plants have a unique spectral reflectance influenced by their structure and composition. The proportion of radiation reflected in different parts of the spectrum depends on the state, structure and composition of the plant. In general, healthy plants and dense canopies will reflect more radiation especially in the near infrared region of the spectrum.

In the visible part of the spectrum (0.4-0.7 µm), plants absorb light in the blue (0.45 µm) and red (0.60 µm) regions and reflect relatively more in the green portion of the spectrum due to the presence of chlorophyll. High photosynthesis activity will result in lower reflectance in the red region and high reflectance in infrared region of the spectrum. In some cases where plants are subjected to moisture stress or other conditions that hinder growth, the chlorophyll production will decrease. This in turn leads to less absorption in the blue and red bands (Tempfli *et al* . 2009; Woldu, 1997). In the NIR portion of the spectrum (0.7-2.5 µm), green plants reflectance increases to 40-60 %. Beyond, (1.3 µm), there are dips in the reflectance curve due to absorption by water in the leaves, more free water result in less reflectance. As the leaves dry out or as the plant ripens or senescence or become diseased or cells die, there is reduction in chlorophyll pigment. That result in the general increase in reflectance in the visible spectrum and a reduction in reflectance in the middle infrared (MIR) portion of the spectrum due to cell deterioration. Thus, the spectral response of crops canopy are influenced by plant health, percentage of ground cover, growth stage, difference in cultural practices, stress condition and the canopy architecture (Verma *et al.*1998). The differential reflectance of green plant in the visible and infrared parts of radiation makes it possible for the detection of green plants from satellite data because other features on earth surface do not have such unique step-like characteristics in the 0.65-0.75 µm spectral range. This signature is unique to green plants only and thus this principle is used in vegetation indices (VIs) (Singh *et al.*2002).

Spectral response of Monitoring pests and diseases patches:

Hyperspectral images have great potential in detecting, diseases-stressed canopies through a spectra-based classification including Minimum Noise Fraction (MNF) and Spectral Angle Mapping (SAM). Field spectra analysis indicated that the most valuable wavelength were between 0.7-0.9 micro meter for remote sensing of the late blight on tomatoes. The mapped diseases distribution at stage in which a minimum of two lesions were on at least one leaf over two lesions were on over half the canopy leaves (Zhang *et al* .,2003). The mapping *Ridolfia segetum* weed patches in sunflower to implement SSWM techniques is feasible with aerial photography acquired when images are taken from 8 to 10 weeks before harvesting (Pena *et al*. 2007). Remote sensing index (NDVI) was used to discriminate between weed infested and weed-free soybean and spectral response of NDVI was higher in weed-infested soybean than in weed-free soybean. Multispectral imagery has the potential for discriminating late-season weed infestations across a range of crop growth stages by using discriminate models developed from other imagery data sets (Koger *et al*. 2003).

Hyperspectral remote sensing techniques are to identify and discern about difference in spectral reflection patterns of winter wheat canopies with and without greenbug damage. The growth conditions, greenbug-damaged wheat canopies had higher reflectance in the visible range and less in the near infrared regions of the spectrum when compared with undamaged canopies (Mirik *et al*. 2006).

The spectral reflectance of aphid infested canopy and health canopy had significant difference in NIR region. In the visible region, the reflectance peak occurred in healthy canopy at around 550-560 nm while this peak was lower by 31%in the aphid infested canopy (Kumar *et al*. 2010). Hyperspectral reflectance spectra between healthy and infested plants showed significant decrease in visible regions (400-700 nm), while increased in the NIR region (770-860 nm). The sensitivity curve shows single peak in blue regions (at about 496 nm) which is characteristic of the Thrips damage (Ranjitha *et al*. 2014).

It is possible to detect the stress caused by the two aphid species and to discriminate between the two aphid-induced stresses in wheat using remote sensing. Ratio-based vegetation indices (based on 800/450 nm and 950/450 nm) were found useful in differentiating the two stresses in wheat (Yang *et al*. 2009)

Prediction models:

Remotely sensed temperature and spectral indices showed that the best stage of prediction model based on leaf area index, dry matter production and grain yield. The cumulative Stress Degree Days (SDD) to showed best correlation with dry matter (r= -0.940) and grain yield (r= -0.939) at period grain formation to harvest stage. Spectral indices (infrared/red, Normalized Difference (ND) showed best correlation to wheat yield prediction is between flowerings to milky stages (Das *et al*. 1993).

A robust yield method was developed for estimating and forecasting wheat yield in Hungary in the period of 2003–2015 using normalized difference vegetation index (NDVI) derived from the data of the Moderate Resolution Imaging Spectroradiometer. Estimation was made at 1-7 weeks before harvest. General yield unified robust reference index (GYURRI) vegetation index was calculated each year using different curve-fitting methods to the NDVI time series. The correlation between GYURRI and country level yield data gave correlation coefficient (r) of 0.985. The differences between the estimated and actual yield data provided by the Hungarian Central Statistical Office were less than 5%, the average difference was 2.5 % (Bognar *et al.* 2017).

Estimate of yield of cotton using linear time series trend and Evapotranspiration (AET) based model for irrigated area and an empirical model between the AET and un-irrigated area and the NDVI (Normalized Difference Vegetation Index) spectral profile data from the LISS I sensor on-board the Indian Remote Sensing (IRS) satellite. The cotton lint yield estimates from the above two different Models 1.2%relative deviation between them and differed by -14.4 and -13.1%, respectively, from the yield estimates given by the Department of Agriculture, Gujarat (Ren *et al*. 2008). F. Lopresti *et al.* (2015) fitted on empirical model was fit between NDVI and yield to estimate wheat yield early 30 days before harvest corresponding to Julian day 289.

An experiment was conducted to study relationship between wheat yield and spectral indices during 1996-97 and 1997-98 at the research farm, CCS HAU Hisar. Variations of ratio vegetation index (RVI), Normalized Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI),Transformed Vegetation Index (TVI), Perpendicular Vegetation Index (PVI) and Greenness Vegetation Index (GVI) have been studied at anthesis stage under different moisture and nitrogen levels. Spectral indices were correlated with crop parameters and it was found that GVI was the best index for yield estimation (r=0.91) (Tempfli *et al*. 2009).

CONCLUSIONS

Hyperspectral analyses have been provided more information from remotely sensed imagery than before. Simple VIs combining visible and NIR bands have significantly improved the sensitivity of the detection of green vegetation. Therefore, each VIs has its specific expression of green vegetation, its own suitability for specific uses, and some limiting factors. Therefore, for practical applications, the choice of a specific VIs needs to be made with caution by comprehensively considering and analyzing the advantages and limitations of existing VIs and then combine them to be applied in a specific environment. In this way, the usage of VIs can be tailored to specific applications, instrumentation used, and platforms. With the development of Hyperspectral and multispectral remote sensing technology, new VIs can be developed, which will broaden research areas. Hyperspectral remote sensing could be used to monitor disease on large scale farms, and it would become more common in the future, especially when images are commercially available and appropriate rapid image processing is possible. Remote sensing indices help to monitor crop health at highly temporal resolution to provide timely agronomic practices.

REFERENCES

1. Bognar, P., Kern, A., Pasztor, S., Lichtenberger, J., Koronczay, D. and Ferencz, C., (2017). Yield estimation and forecasting for winter wheat in Hungary using time series of MODIS data. *International journal of remote sensing*, 38(11): 3394-3414.
2. Das, D.K., Mishra, K.K. and Kalra, N. (1993). Assessing growth and yield of wheat using remotely sensed canopy temperature and spectral indices. *International Journal Remote of Sensing* 14(17): 3081-3092.
3. Hunt Jr.E.R.,Doraiswamy P.C., McMurtrey J.E., Daughtry C.S.T. and Perry E.M. (2013). A visible band index for remote sensing leaf chlorophyll content at the canopy scale. *International Journal of Applied Earth Observation and Geo information* 21: 103–112
4. Jiao, X. F., Yang, B. J., Pei, Z. Y. and Wang, F. (2005). Monitoring crop yield using NOAA/ AVHRR-based vegetation indices. *Journal of the Chinese Society of Agricultural Engineering*, 21(4): 104-108.
5. Koger, C.H., Shaw, D.R., Watson, C.E. and Reddy, K.N. (2003). Detecting late-season weed infestations in soybean (Glycine max). *Weed Technology*. 17(4): 696-704.
6. Kumar J., Vashisth A., Sehgal V.K., Gupta V.K. (2010). Identification of aphide infestation in mustard by hyperspectral remote sensing. *Journal of Agricultural Physics*10:53–60.
7. Liu, C., Sun, P.S. and Liu, S.R., 2016. A review of plant spectral reflectance response to water physiological changes. *Chinese Journal of Plant Ecology*. 40: 80-91.
8. Lopresti, M.F., Di Bella, C.M. and Degioanni, A.J. (2015). Relationship between MODIS-NDVI data and wheat yield: A case study in Northern Buenos Aires province, Argentina. *Information Processing in Agriculture*, 2(2): 73-84.
9. Mirik, M., MichelsJr, G.J., Kassymzhanova-Mirik, S., Elliott, N.C. and Bowling, R. (2006). Hyperspectral spectrometry as a means to differentiate uninfested and infested winter wheat by greenbug (Hemiptera: Aphididae). *Journal of economic entomology*, 99(5): 1682-1690.
10. Pena-Barragan, J.M., Lopez-Granados, F., Jurado-Exposito, M. and Garcia-Torres,L.(2007). Mapping Ridolfiasegetum patches in sunflower crop using remote sensing. *Weed Research*, 47(2): 164-172.

11. Peñuelas, J., Filella, I., Biel, C., Serrano, L. and Save, R. (1993). The reflectance at the 950–970 nm region as an indicator of plant water status. *International journal of remote sensing*, *14*(10): 1887-1905.
12. Ranjitha G., Srinivasan M.R. and Rajesh A. (2014). Detection and estimation of damage caused by ThripsThripstabaci (Lind) of cotton using hyperspectral radiometer. *Agrotechnology* 3: 1–5.
13. Ray S.S., Pokharna S.S and Ajai. (1999). Cotton yield estimation using agromiteorological model and satellite derived spectral profile. *International Journal Remote Sensing* 20: 2693-2702.
14. Ren, J., Chen, Z., Zhou, Q., Tang, H. (2008). Regional yield estimation for winter wheat with MODIS-NDVI data in Shandong, China. *International Journal Application Earth Observation Geoinformation*10 (4): 403–413
15. Richardson, A.D., Aikens, M., Berlyn, G.P. and Marshall, P. (2004). Drought stress and paper birch (Betulapapyrifera) seedlings: effects of an organic biostimulant on plant health and stress tolerance, and detection of stress effects with instrument-based, noninvasive methods. *Arboriculture & Urban Forestry*, 30(1):52.
16. Riedell, W.E. and Blackmer, T.M. (1999). Leaf reflectance spectra of cereal aphid-damaged wheat. *Crop Science*, 39(6): 1835-1840.
17. Rouse Jr, J., Haas, R.H., Schell, J.A. and Deering, D.W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. NASA Goddard Space Flight Center 3rd ERTS-1 symposium. 1 (A): 309-317.
18. Sawasawa, H.L.A. (2003). Crop yield estimation: Integrating RS, GIS, and management factors. A Case study of Birkoor and Kortgirit mandals-Nizamabad District, India, M.Sc thesis, ITC.
19. Singh, R.A.N.D.H.I.R., Semwal, D.P., Rai, A. and Chhikara, R.S. (2002). Small area estimation of crop yield using remote sensing satellite data. *International Journal of Remote Sensing*, *23*(1): 49-56.
20. Tempfli, K., Huurneman, G., Bakker, W., Janssen, L.L., Feringa, W.F., Gieske, A.S.M., Grabmaier, K.A., Hecker, C.A., Horn, J.A., Kerle, N. and van der Meer, F.D.,(2009). Principles of remote sensing: an introductory textbook. ITC.
21. Verma, K.S., Saxena, R.K., Hajare, T.N. and Kumar, S.R. (1998). Gram yield estimation through SVI under variable soil and management conditions. *International Journal of Remote Sensing*, 19(13): 2469-2476.
22. Wall, L., Larocque, D. and Leger, P. M. (2007). The early explanatory power of NDVI in crop yield modeling. *International Journal of Remote Sensing*, 29: 2211−2225.
23. Wang, H., Xiaohe, G., Wang, J., & Dong, Y. (2012). Monitoring winter wheat freeze injury based on multi-temporal data. *Intelligent Automation & Soft Computing*, 18: 1035–1042.
24. Woldu, T., 1997. Remote sensing of Biomass Production, Radiation Distributions, and Rainfall Patterns. Senior thesis Report, Physics Department, University of Asmara.
25. Yang Z, Rao MN, Elliott NC, Kindler SD, Popham TW (2009) Differentiating stress induced by greenbugs and Russian wheat aphids in wheat using remote sensing. *Computers and Electronics in Agriculture* 67: 64-70.
26. Zhang, M., Qin, Z., Liu, X. and Ustin, S.L. (2003). Detection of stress in tomatoes induced by late blight disease in California, USA, using hyperspectral remote sensing. *International Journal of Applied Earth Observation and Geoinformation*. 4(4): 295-310.