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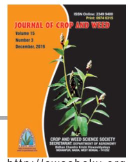

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NDVI derived LAI model: A novel tool for crop monitoring

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ABSTRACT

Over the period of time agriculture undergone metamorphosis.At present,many agriculture issues are being tackled by sophisticated sensor-based technologies. Normalized Difference Vegetation Index (NDVI) derived Leaf Area Index (LAI) is one such optical sensor-based simulation model which bridges optical behavior of vegetation with highly dynamic biological system. Higher plants exhibit differential response to electromagnetic spectrum as they have differential ratios of plant pigments which have distinct absorption, transmission and reflection of light. Based on this principle, NDVI derived LAI model is being used in prediction of various cropping activities and it exhibited high degree of positive correlation with ground truth assessment. Hence, NDVI derived LAI model would be suitable strategy for vegetation surveillance, stress assessment, pest and disease scouting as well as acreage and production forecasting of agriculture crops with high degree of accuracy.

Keywords: Estimation, Forecast, LAI, NDVI, Sensor, Stress-assessment

In the contemporary world information gathered by aerospace sensors has become a necessity in various real time investigations and fields' application (De-beurs and Townsend, 2008). Crop production being the highly complex system, understanding its dynamics over large area in real time situation is crucial thing in management of production system. In the eve of uncertainties of climate knowing production potentiality in advance is imperative thing for framing suitable strategies to handle unforeseen events. Crop monitoring under diversified cropping activities in real time situation is tedious as well as time consuming and also highly impossible to do with at higher accuracy (FAO, 2018). Therefore, vegetation monitoring through air-based sensors is one among the priorities of today's agriculture (Zhang *et al*., 2018). Remote sensing is a quick, cheap and straight forward tool that is used to access distantly located plant development process and retrieve information about plant growth for subsequent utilities (FAO, 2018). Several studies conducted on vegetation monitoring indicated the existence of strong and positive correlation of remotely sensed data with the biophysical behavior of real-world vegetation (Matese *et al*., 2013; Feng and Liu., 2015 and Matzrafi *et al*., 2017). For an instance, a study conducted by Rao *et al*. (2006) reveled that, predicted and actual LAI exhibited meager deviation under two sensor system *viz.,* LISS-III and Hyperion, both the sensor registered LAI are in close agreement with the field measured one. However, higher accuracy of Hyperion might be due to the higher resolution of scanner (Table 1). Data acquired by remote sensing techniques has paramount importance in agriculture application due to its unique capability of recording data both under visible as well as invisible band width (*i.e.* ultraviolet, reflected infrared, thermal infrared and microwave etc.) of electromagnetic spectrum. Good numbers of dedicated satellites are employed for agriculture and natural resource management in India (Table 2) and are performing varieties task with varied accuracy. The data acquired by the sensors on certain phenomenon could not be observed and recorded by seen by human eye under field condition, in such situation remotely sensed data act as good and autunitic source of vigilance on real time dynamics of agro-ecosystem.

Crop acreage and production estimation and its forecasts are crucial to policy makers for the planning of import-export strategies for monitoring of food supply. It enables the planners to make necessary arrangements for unseen events of food and social security. Crop production being the phasic process, dynamics of each crop phase has its own role to play in deciding ultimate productivity. In the absence of real time reliable information on crop status taking steps towards formulating agriculture policies are highly difficult. Traditionally way of data accusation through crop cutting experiments is highly tedious to make estimation on crop acreage and production (FAO, 2018), it includes an extensive travel and various interpolation methods based on the sample taken. Traditionally the department of agriculture and its lane officials visit the village where they inquire about crop acreage and expected yield. Based on these types of sampling the results are projected to acquire the acreage and yield information. This methodology, though prevalent from a long time is neither very accurate nor very scientific.

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Yield depends on various biotic and abiotic factors such as climatic, soil, management *etc*, some factor may or may not change over two successive years, however, some are highly dynamic (climate). Crop production being the highly complex and interdependent process, slight change in each factor has reciprocal influences on dependent factors. Under such situation, adoption of traditional methodologies adopted for yield prediction is vague and unscientific. Hence, real time vegetation monitoring facilitates us to have in-depth understanding about interactive and complex agriculture system. Effectively utilization of contemporary techniques of young and front-line sciences such as satellite remote sensing and crop simulation modeling in such decision making timely and cost-effective investigations are order of the day. Remote sensing yields space data on various aspects of the earth surface, space data acquired in temporal mode could be used in monitoring crop condition, soil information, biotic and abiotic stress monitoring (ISRO, 2020).

Yield is the manifestation of yield attributes; performance of crop in yield attributing is the direct reflection of growth during vegetative phase (Kumar *et al*., 2015). Every vegetation has a unique spectral signature; usually vegetation differs in their reflectance values as it is governed by color, density, angle of leaf inclination (Mo *et al*., 2003). Further, within the species plants exhibits identical spectral signature for stressed and healthy vegetation. These unique reflectance characters of vegetation could be due to variation in leaf pigments (Gitelson *et al*., 2003) cell structure and water content. In the visible range the reflectance is relatively low as the majority of light is absorbed by the leaf pigments. Chlorophyll strongly absorbs energy in the blue and red wavelengths and reflects more green wavelengths, while in infra-red rage of electromagnetic spectrum healthy vegetation reflects higher near infrared (NIR) region than in the visible region due to the cellular structure of the leaves, specifically the spongy mesophyll. Therefore, healthy vegetation can be easily identified by the high NIR reflectance and generally low visible reflectance (Figure 1). Therefore, the unique reflectance characteristics of plant under varied band width helps to identify the type and status of vegetation on the earth. Based on the reflectance behavior at red and rear infra-red, satellite imageries of the vegetation depict mosaic images of land mass scanned (Figure 2). From the information stored in the form of spectral signature various vegetation indices can be synthesized, among them normalized difference vegetation index (NDVI) is the most common index used to analyze behavior of vegetation in remotely sensed data. NDVI quantifies both quality and quantity of the vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs). The notation of NDVI is as fallow.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

In real field situation, quantity of photosynthetic apparatus could be quantified by measuring leaf area index (LAI), it acts as key variable functionally related to plant biomass production (Fan *et al*., 2009) as it determines the photosynthesis, respiration, and transpiration of vegetation (Laliberte *et al*., 2011). The traditional, direct and destructive method of measuring LAI is tedious and time-consuming process. Hence, alternative and more specialized NDVI is widely used, spectral reflectance index shown to be a good estimator of LAI and is used to estimate LAI indirectly (Fan *et al*., 2009).

LAI is an important biophysical variable used to assess crop yield as it influences the physical and chemical and biological processes like photosynthesis, respiration and evapotranspiration and several dynamic-process like crop-growth, absolute growth rate, relative growth rate and net assimilation rates are bound to influence by plant leafiness hence, LAI is the only indices which can effectively bridge dynamic-process of plant growth to remote-sensing irradiative models. A study conducted by Verma *et al*. (2003) to estimate wheat acreage and production through NDVI derived LAI model indicated that area and production estimated by NDVI derived LAI model found to be relatively accurate and deviations observed in the tolerable levels in all the experimental sites (Table 3). Further, in 2001, Cheng *et al*. (2003) also opined that, the NDVI is the most stable vegetation index for estimating the LAI. It was observed from the study conducted by using different plant of wheat (erectophile-type, middle-type and planophile-type) to calculate LAI by using NDVI values indicated that NDVI can be used to indirectly monitor LAIT (Tan *et al*., 2020). Therefore, this review through some light on scientific work was done on NDVI derived LAI and its utility in vegetation monitoring by bringing together published works and discussed by using systematic review approach.

VEGETATION MONITORING

The NDVI is a commonly used vegetation index in regional and global vegetation assessments, it not just indicates canopy structure and LAI, it is also found to be the precise tool for quantification of canopy photosynthesis (Grace *et al*., 2007). The high degree of accuracy in vegetation identification is possible through NDVI approach due to great disparity in ratios of photosynthetic pigments (chlorophylls and carotenoids)

Table 1: Field validation of remote sensed LAI value for cotton, rice and sugarcane (Rao *et al*., 2006)

Measured			Predicted					
			LISS-III			Hyperion		
Cotton	Rice	Sugarcane	Cotton	Rice	Sugarcane	Cotton	Rice	Sugarcane
1.92	2.42	3.52	2.22	2.71	3.00	1.81	2.58	3.45
1.58	2.08	3.18	2.09	2.53	2.99	1.69	2.38	3.12
1.54	2.04	3.14	1.98	2.38	2.98	1.55	2.22	3.08
1.56	2.06	3.16	1.98	2.38	3.01	1.65	2.32	3.09
1.65	2.15	3.25	1.99	2.4	3.03	1.69	2.39	3.18
1.78	2.28	3.38	2.11	2.57	3.03	1.72	2.43	3.31
1.85	2.35	3.45	2.17	2.65	3.01	1.77	2.52	3.38
1.89	2.39	3.49	2.18	2.66	2.97	1.78	2.53	3.42
1.96	2.46	3.56	2.26	2.76	3.03	1.85	2.64	3.65
1.99	2.49	3.59	2.29	2.81	3.06	1.88	2.7	3.65
2.01	2.51	3.61	2.52	3.13	3.08	2.09	3.06	3.65
2.00	2.5	3.59	2.52	3.13	3.07	2.09	3.06	3.65

Table 2: Remote sensing satellites of Indian Space Research Organization involved in agriculture applications

Satellite Type	Satellite	Objectives
Multispectral imaging satellite	Resourcesat-2 & Resourcesat-2A	Multispectral imaging for crop production forecast, land, water and natural resource inventory and management, and disaster management support
Cartography satellite	Cartosat-1	High resolution cartographic mapping, digital elevation mapping – drainage and irrigation networks, topographic mapping and contouring
Radar imaging	RISAT-1	All weather imaging capability targeted for kharif crop (June to November) during south-west and north-east monsoon seasons. Flood and natural disaster management
Meteorological forecasting	Kalpana-1	Comprehensive weather status reporting and forecasting
Meteorological observation	INSAT-3D & INSAT-3DR	Improved meteorological observations including vertical – temperature and humidity – atmosphere weather forecasting and disaster warning

Source: Press Information Bureau-Government of India (2017)

Table 3: Comparison of wheat acreage and agro-met-spectral trend production forecast with Department of Economics and Statistics estimates (Verma *et al.,* 2003)

District	Acreage (000' ha)			Production (000't)		
	Predicted	DES	RD %	Predicted	DES	RD %
Ambala	80.22	78	2.77	311.73	272	12.75
Bhiwani	140.75	137	2.66	519.09	451	13.12
Faridabad	136.46	134	1.8	563.58	539	4.36
Fatehabad	169.24	174	-2.81	703.68	757	-7.58
Gurgaon	126.67	137	-8.16	475.52	480	-0.94
Hisar	190.29	207	-8.78	806.07	887	-10.04
Jhajjar	102.56	105	-2.38	377.86	402	-6.39
Jind	203.14	207	-1.9	851.97	895	-5.05
Kaithal	176.26	153	13	755.45	688	8.93
Karnal	166.81	167	-0.11	708.94	774	-9.18
Kurukshetra	107.16	109	-1.72	484.15	506	-4.51
Sirsa	235.7	244	-3.52	989	1015	-2.63

Table 4: Effect of soil fertility level on NDVI at various growth stages of soybean (Patil *et al*., 2007)

Treatments	NDVI				
	39 DAS	55 DAS	67 DAS	76 DAS	88 DAS
N_0P_0	0.267	0.461	0.567	0.493	0.408
N_{30}	0.320	0.485	0.583	0.525	0.483
P_{60}	0.412	0.515	0.650	0.567	0.508
$N_{30}P_{60}$	0.44	0.585	0.695	0.587	0.523
N_{45}	0.483	0.583	0.723	0.617	0.580
N_{60}	0.553	0.603	0.752	0.633	0.602
P_{120}	0.602	0.638	0.755	0.658	0.642
$N_{60}P_{120}$	0.650	0.675	0.788	0.723	0.643
SEm±	**0.031**	**0.022**	**0.016**	**0.019**	**0.018**
CD at 5 %	**0.09**	**0.063**	**0.047**	**0.056**	**0.053**

Table 4: Comparison of wheat acreage and agromet-spectral trend production forecast with Department of Economics and Statistics estimates (Verma *et al*., 2003)

District	Acreage (000' ha)			Production (000't)		
	Predicted	Actual	RD %	Predicted	Actual	RD %
Ambala	80.22	78	2.77	311.73	272	12.75
Bhiwani	140.75	137	2.66	519.09	451	13.12
Faridabad	136.46	134	1.8	563.58	539	4.36
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Sirsa	235.7	244	-3.52	989	1015	-2.63

Table 5: Predicted yield and observed yield of wheat model from ground truth sites (Patil *et al*., 2012)

Sl. No.	Site No.	Model predicted yield at GT sites(kg ha^{-1})	Observed yield at GT sites (kg ha^{-1})
1	3	2161	1809
2	5	3411	3600
3	6	2625	2830
4	8	2727	2750
5	9	4549	4183
6	10	2634	2448
7	11	2781	3050
8	12	2648	3246
	Mean	2942	2990
Relative deviation		-	-1.59

Table 6: Estimates of sugarcane area through remote sensing and relative deviation in comparison with Department of Agriculture and Department of Economics and Statistics (Chandrasekhar, 2009)

Sl. No.	Sugarcane classes	Estimated area (ha)					
		Gokak			Raibag		
		38443	38718	38808	38443	38718	38808
1	Matured cane	3013	0	2893	4530	9631	4445
2	Grand growth cane	2530	11347	2950	3141	4153	2812
3	Early stage cane	1428	5448	18972	7798	3960	20192
4	Flowering cane	0	995	0	0	0	0
5	Total estimated area	20067	17790	24815	15469	17744	27449
6	As per Dept.	18613	18613	25890	15580	18313	26650
7	Relative deviations (%)	7.8	-4.4	-4.2	-0.7	-3.1	3

in higher plants. As a result of it, each plant species on the earth responds distinctly to given range of electromagnetic spectrums. Chlorophyll *a* absorbs blue-violet region of electromagnetic spectrum, while chlorophyll *b* absorbs red-blue light. Neither chlorophyll *a* or chlorophyll *b* absorb green light of electromagnetic spectrum and green rage is totally reflected or transmitted by chlorophyll pigment. Therefore, higher plants with chlorophyll pigments in their leaves appear green color (Figure 2). On the other side, carotenoids absorb light in the blue-green and violet region of electromagnetic spectrum and reflect the high amount of red and its associated ranges (orange and yellow) (Figure 2). This unique spectral response of plant to electromagnetic spectrum helps in identification of mixed vegetation of very close proximity. It was evident for the work conducted by Gitelson *et al.* (2003) significantly higher mean reciprocal reflectance value was observed under the higher chlorophyll content than carotenoid under identification of mixed vegetation. Da-Silva *et al.* (2020) argued that, NDVI had good adjustments in most of the thematic classes of land use land cover and was found to be the best choice of the vegetation index for land use and occupation classification. In another study, the LAI estimated by using vegetation index extracted from the remote sensing image has a good correlation with measured LAI of real field situation, of the various vegetation monitored the best fitting indices for Alpine Pine forest, Oak forest, Spruce–fir forest and Yunnan Pine forest were RVI (R2 = 0.6251), DVI (R2 = 0.7903), WDRVI (R2 = 0.7439), NMDI (R2 = 0.7515), and RVI (R2 = 0.6330), respectively (Yu *et al*., 2019). The vegetation dynamics of 11 different sites (six deciduous forests sites, four crop sites and one grasslands site) monitored for LAI estimation indicated that, the NDVI produced significantly better LAI estimations than the EVI and NIRv in all type of vegetation studied (Qiao *et al*., 2019). Crop identification vis-à-vis yield estimation of three field crops (rice, wheat and corn) in three different locations of Nanpan River basin in Yunnan Province of China showed higher reliable estimation of yield through NDVI derived LAI model when crops were at heading, flowering, and grain filling stages of the crops (Huang *et al*., 2014). Production forecasting is another advantage of NDVI derived LAI model, yield forecasted through NDVI based cropland identification in Mediterranean African countries reveled that, yield estimation showed that relatively high degree of positive correlations between crop yield and mean NDVI of individual crops and cropping system (Masell and Rembol, 2001). The accuracy of predication could be enhanced by identifying critical growth phases of the crop, the higher reliability of yield prediction in sugarcane could be achieved between 210 to 270 days after plantation (Singla *et al*., 2018). Crop survey, land use land cover estimation is the order of the day to study the land use dynamics and quantification of uncertainties of agro-ecosystem, simultaneous inclusion of NDVI and LAI yield profound accuracy in the classification of fallow land, barren land, settlement; degraded forests and forest blank (Sinha *et al*. 2015). Under high resolution remote sensing intra species varietal differentiation is also possible through NDVI approach. Crusiol *et al*. (2016) observed differential response on soybean cultivar Embrapa 48 (less drought-sensitive) and BR 16 (more drought-sensitive) to NDVI values at active growth stage. Based on the study conducted by various workers it could be inferenced that, NDVI has profound advantages over traditional crop monitoring practices as it provides real time dynamics of the study area, time and resource needs to ascertain vegetation vigilance can be substantially reduced besides increasing accuracy of estimation.

STRESS MONITORING

Stress is a major focus of current agricultural research (Olukayode *et al*., 2018). Biotic or abiotic stress

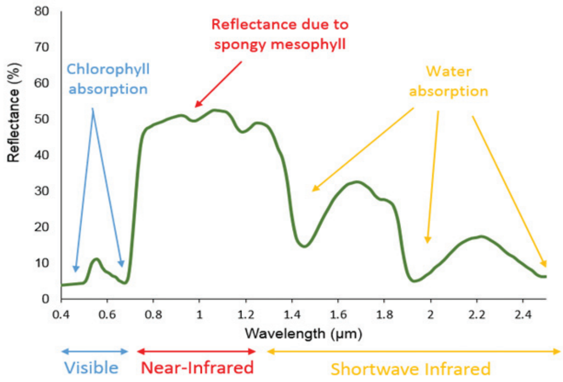

Fig. 1: **Spectral response of vegetation to electromagnetic spectrum (GSP 2016 Introduction to remote sensing, Humbildt State University)**

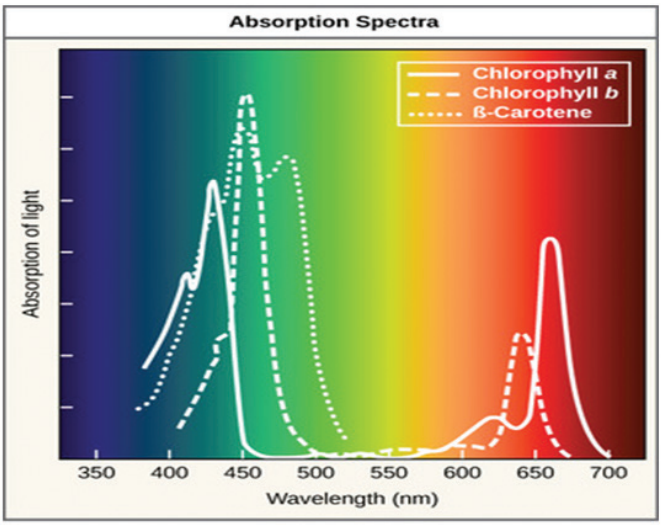

Fig. 2: **Spectral response of chlorophyll and carotenoid pigments [(Optimal absorption of light occurs at different wavelengths for different pigments. Image modified from "The light-dependent reactions of photosynthesis: by OpenStax College, Biology (CC BY 3.0)]**

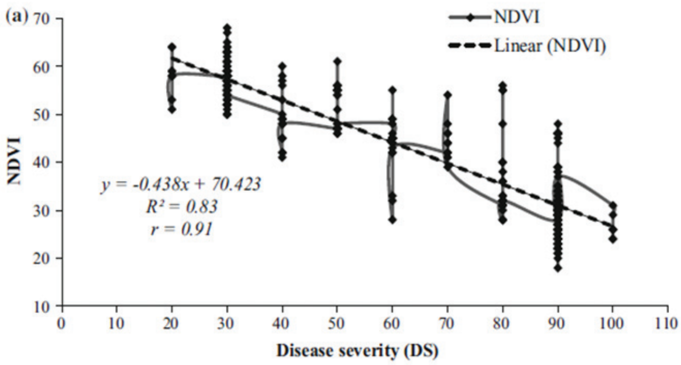

Fig. 3: **Scatter plot of NDVI versus visual disease scores for the mapping population 'YS116 9 Sonalika' at GS77 (Kumar *et al.*, 2016)**

bound to influences the alterations in the concentrations of chlorophyll, carotenoid and anthocyanin (Bravo *et al*. 2003; Franke and Menz, 2007). Soil moisture, light intensity, mineral nutrition, pest and disease are the major means of plant stress. The NDVI is an important and frequently used index for the monitoring of vegetation as influenced by various factors of production, because NDVI is ultimate reflection of vegetation quality as it is governed by leaf chlorophyll content (Gitelson *et al*., 2003) and chlorophyll development is again governed by the leaf water content (Li *et al*., 2018). Water adequacy imparts healthy vegetation therefore, it is a suitable tool for monitoring plant growth (Stone *et al*., 2001) essentially in detecting abiotic stress in vegetation (Genc *et al.,* 2013 and Spitkó *et al.,* 2016). Remote sensing techniques are useful tools to monitor the growth and response of the crop to water stress (Stone *et al*., 2001). Lower NDVI values in cluster bean recorded lower value of NDVI than unstressed one (Silva *et al*., 2016). Light intensity has profound influence on crop growth (Bayat *et al*., 2018), based on requirement of light, higher plants are classified into, helophytes and sciophytes, cocoa exhibited higher values of NDVI under un-shaded portion of the study area than the values in the shaded portion of the study area (Olukayode *et al*., 2018), it could be due to proper development of chlorophyll under un-shaded area with bright sunlight. Similarly, several studies generated the relationship between NDVI and the soil mineral contents, decrease in NDVI is directly proportional to the percentage and composition of the soil minerals (Carter and Knapp, 2001; Carter and Spiering, 2002; Carter and Estep, 2002 and Zhao *et al*., 2003). In another study, Patil *et al*. (2007) illustrated the influences of mineral nutrition on NDVI values, treatment received relatively higher and optimum amount of fertilizer to soybean plants per unit area registered the higher NDVI compared to treatments with lower doses of plant nutrient and was due to higher level of nutrients are attributed to the better chlorophyll development and it ultimately expressed through NDVI values (Table 4). Vegetation indices are determined by contrasting intense chlorophyll pigment absorptions in the red against the high reflectivity of plant materials in the NIR (Mirik *et al*., 2007). Vegetation indices being the key variables greatly influenced by the concentration of total chlorophyll of the vegetation (Apprico, 2002; Sims and Gamon, 2002; Apprico *et al*., 2000). Significant reduction in total chlorophyll content in biotical stressed plant was earlier reported by Cárdenas and Gallardo (2016). The variation in spectral response of crop canopy in disease incidence leads to chlorosis, the presence of coloured pustules and other symptoms (Bravo *et al*. 2003) and was proved in study conducted by Kumar *et al*. (2016) by showing highly negative correlation between NDVI and per cent disease severity of spot blotch disease of wheat (Figure 3) again based on the outcomes of soybean disease monitoring with leaf reflectance. Bajwa *et al.* (2017) argued NDVI was a promising potential indicator of the disease.

Acreage Estimation and Yield Prediction

Status of agricultural production well before the harvest is essential to make necessary strategies on unforeseen events of food and societal security. It has been the established technique of production forecast in many developed countries in the world *viz.*Swaziland (Mkhabela and Mkhabela 2000), Zimbabwe (Unganai and Kogan 1998), Kenya (Lewis *et al*., 1998), Spain (Vicente-Serrano *et al*., 2006), and Canada (Wall *et al*., 2008). Verma *et al*. (2003) estimated wheat area and yield by using NDVI derived LAI model of wheat crop in Hisar, India; they found tolerable levels of relative deviation between actual and predicted area and production in all the experimental sites (Table 4), slight deviation in actual and predicted which was due to improper illumination of study area as they were located in the sub mountainous region. In Karnataka, Potdar (2010) conducted a study on estimation of the acreage of red gram crop of Chittapur thaluk, from the study they reported that area occupied by the red gram crop during 2006-07 and 2007-208 was 51626 and 50713 ha, respectively as against one which observed by the Department of Economics and Statistics which was 47574 and 48388 ha, during both years of study relative deviation observed was 7.84 and 4.58 per cent during 2006-07 and 2007-08, respectively (Table 5). Further, Patil *et al*. (2012) also observed minimal deviation between yields predicted through NDVI derived LAI model to yield under real field experimentation (Table 5). Under mixed stand, area under chilli was conducted by Malleshwari *et al*. (2006), from the study it was observed that the acreage estimates using NDVI derived LAI model showed a relative deviation of -18.56 and -7.27 per cent in Kundagol and Hubbli thaluks, respectively when compared to the one reported by Department of Horticulture of Karnataka State.

In sugarcane Chandrashekar (2009) conducted a study on estimation of acreage of different classes of sugarcane and in all the stages of the crop growth they found that very minimal relative deviation when compared to the ground truth data as Department of Agriculture and Department of Economics and Statistics (Table 6), similarly, minimal deviation in between estimated and actual yield of rice by using NDVI derived LAI model (Murthy *et al.,* 2011).

CONCLUSION

Based on the experimental findings of various scientific workers, it was known that NDVI is an important vegetation index which describes the quality of the vegetation. Accuracy of the model depends upon the quality of the remotely sensed image and accuracy of the ground truth recorded data. NDVI derived LAI model is excellent option for acreage estimation compared to the production and productivity assessment.

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