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Estimation and counter- validation of LISS-III derived leaf area index in Deltaic vegetation

Abhisek Santra*, Shreyashi Santra Mitra, Suman Sinha

Department of Civil Engineering, Haldia Institute of Technology, ICARE Complex, HIT Campus, Haldia-721657, Midnapore(E), West Bengal, India

* *Corresponding author's E-mail: avisek.santra@gmail.com*

ABSTRACT

Leaf area index (LAI), a dimensionless biophysical variable is considered as one of the most important factors in characterizing canopy structure. It estimates the amount of foliage area per unit of ground area and helps indirectly to assess biomass and energy balance in an ecosystem. Remote sensing techniques established a strong correlation between the vegetation reflectance characteristics in red and near infra-red bands and LAI. Good number of image derived vegetation indices has been applied so far to estimate LAI successfully. In this paper correlation is established between field-collected LAI and three soil adjusted vegetation indices, i.e., SAVI, MSAVI and OSAVI derived from IRS-LISS-III data in deltaic ecosystem in Sagar Island of West Bengal, India. LAI was estimated from OSAVI for the whole island as OSAVI yielded best result (R^2= 0.92). Coarse resolution MODIS LAI (MOD 15A3) product was counter-validated with respect to the LISS-III derived LAI image following the upscale validation approach. Out of the six best-fit models applied, the logistic regression showed strong positive correspondence between the two products (R^2 = 0.71). Uncertainty of the model was also assessed and probable reasons were identified.

Keywords: SAVI; LAI; LISS-III; MODIS; ATCOR-2.

INTRODUCTION

Leaf area index (LAI) is one of the most important parameters characterising a canopy and is a major attribute in understanding ecosystem. It is a dimensionless biophysical variable and is defined as the one-sided green leaf area per unit ground area (Pandya *et al*. 2006; Chaurasia *et al*. 2011). It quantifies the amount of foliage area that governs evapotranspiration, photosynthesis, energy balance, and helps to estimate biomass in an ecosystem (Maas 1991; Bonan 1993; Nemry *et al.* 1996; Liu *et al.* 1997; Chaurasia *et al.* 2011). LAI strongly correlates with the fraction of absorbed photosynthetically active radiation (fAPAR) – the energy available for Net Primary Production (NPP). Together they control water, carbon and energy exchange between vegetation and atmosphere (Running *et al.* 1996). Thus, it constitutes a key parameter for forest growth (Jarvis & Leverenz 1983; Monteith 1977), responds rapidly to different stress factors and climatic conditions and serves as a useful indicator to characterise the condition of forest ecosystem in vision of global change (Myneni *et al.* 1997; Stenberg et al. 2004). There are many methods of estimating LAI directly based on leaf sampling and litter fall collection (Clough *et al*. 1997; Green *et al.* 1997). However, these methods are time-consuming and need rigorous ground validation from the inaccessible parts of forest and mangrove ecosystems. With the advent of remote sensing and GIS techniques, the scenario changed a lot. Remote sensing established the fact that there is a strong correlation between a red to near infra red (NIR) transmittance ratio and LAI (Jordon 1969). It can be inferred that the spectral measurements are strongly related to the amount of leafy biomass or leaf area index (Tucker 1979). Several vegetation indices have been used so far to estimate LAI indirectly, for example, normalised difference vegetation index (NDVI) (Tucker 1979), soil adjusted vegetation index (SAVI) (Huete 1988), modified soil adjusted

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vegetation index (MSAVI) (Qi *et al.* 1994), optimized soil adjusted vegetation index (OSAVI) (Rondeaux *et al.* 1996), weighted difference vegetation index (WDVI) (Clevers 1991), enhanced vegetation index (EVI) (Liu & Huete 1995). However, no universal model relating LAI and VIs has been developed yet (Qi *et al.* 2000; Papadavid *et al*. 2013). This fact directs remote sensing users to develop equations and models for each ecosystem or region and validate or compare their results substantially with true measurements of LAI or with other derived LAI products. For this purpose, improved vegetation indices like SAVI, MSAVI, OSAVI, WDVI, WDRVI are used because these indices minimize the impact of soil, atmospheric and topographic effects (Qi *et al.* 2000; Kovacs *et al*. 2004; Papadavid *et al.* 2013; Maki & Homma 2014). In deltaic vegetation mixed with mangroves, orchards and agricultural crops, remote sensing data is considered to be an important source of LAI measurement. In this regard, Landsat 8, Sentinel 2A, Rapid Eye and hyperspectral data are applied to assess the LAI for different types of vegetation, grass and agricultural crops (Juniansah *et al.* 2018; Alexandre *et al.* 2018; Ovakoglou *et al.* 2018; George *et al*. 2018 Pasquolotto *et al.* 2019,). The area chosen for this study is Sagar Island which is not only accessible but also having a combination of homogeneous crop and vegetation pattern. The island is mostly composed of agricultural fields where paddy is the major crop grown. Besides, settlements are found coupled with orchards. Only the fringe areas of the island, specifically at the east, mangroves are present (Mondal *et al.* 2019). Therefore, in this study, three versions of SAVI are applied to estimate LAI from LISS-III images in deltaic ecosystem. The other aforementioned indices are mostly applied on crops like barley, maize, corn, soybeans, etc. The SAVI with its siblings yielded better results in case of paddy (Maki & Homma 2014).

MATERIALS AND METHODS

Study Area

River delta is not only important from productivity perspective, but also known for floral and faunal diversity. For the present study, the deltaic vegetation of lower Indian Sunderban, especially the Sagar Island was chosen because of its vast importance in multi-direction. The Sagar Island is the largest island of the Sunderbans deltaic complex. It is surrounded by Hugli River in the north and west, Muri Ganga River in the east and Bay of Bengal in the south. These rivers are the sources of sedimentation for this island (Gopinath 2010). The latitudinal and longitudinal extents are 21°37´ N to 21°52´ N and 88°02´ E to 88°10´ E respectively (Fig. 1). The elongated-shape island length is nearly 30 km, while the maximum width is around 12 km. The island is having daily tidal fluctuations and was affected by tropical cyclones many times in the past (Gopinath 2010). The agricultural land is the mono-crop land where paddy is only grown (Mondal *et al*. 2019). Mangroves are found mainly at the boundary areas of the eastern part of the island. The island is also gaining importance in terms of tourism and religious interests.

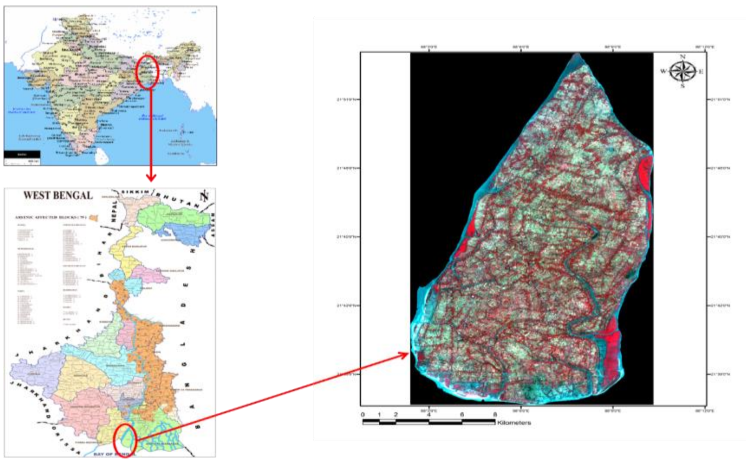

Fig. 1. Study area.

Database

To estimate LAI of the deltaic ecosystem of Sagar Island, the satellite data of linear imaging self scanner – III (LISS-III) onboard IRS P6 Resourcesat – 1 was used. The LISS-III data is a four-band multispectral data which operates in three spectral bands in visual near infra red (VNIR) and one band in short wave infra red (SWIR) spectrum with 23.5 m spatial resolution and a swath of 141 km (Table 1). For validation purpose, the combined

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moderate resolution imaging spectroradiometer (MODIS) LAI (MCD15A3) 4-day level-4 global data was used. The data covers the whole globe with a spatial resolution of 1 km (Table 2).

Table 1. LISS-III product information.

Name of Sensor	**Linear Imaging Self Scanner - III (LISS-III)**
Onboard Satellite	IRS P6 Resourcesat-1
Nature of Data	Ortho-corrected Georectified (Geotiff)
Date of Data Acquisition	23rd November, 2009
Spatial Resolution	23.5 m
Spectral Resolution	B2 0.52 - 0.59 µm (Green) B3 0.62 - 0.68 µm (Red) B4 0.77 - 0.86 µm (Near Infrared) B5 1.55 - 1.70 µm (Shortwave Infrared)
Radiometric Resolution	7 Bits. SWIR band has 10 bits quantization, selected 7 bits out of 10 bits is transmitted by the data handling system
Swath	141 Km
Temporal Resolution	24 Days

Table 2. MODIS LAI (MCD15A3) product information

Name of Sensors	**Terra and Aqua MODIS**
Image Dimension	1200 Rows x 1200 Columns
Data Format	HDF-EOS
Projection	Sinusoidal
Spatial Resolution	1 Km
Temporal Coverage	4 Days Composite
Radiometry	8 Bits
Valid Range	0 - 100
Scale Factor	0.1

Method

Initially, the two scenes of the same data were merged together and clipped to get the study area. At first, the image was converted to radiance image considering the sensor gain and bias factors. Radiometric correction helps to remove the effects generated by solar illumination conditions, atmospheric scattering and absorption (Santra et al. 2019). Thus, the radiance image was atmospherically corrected using ATCOR-2 atmospheric model. ATCOR-2 supports wide range of sensor data, e.g. Landsat series, LISS-III, Sentinel 2A etc. ATCOR-2 is a spatially adaptive fast atmospheric correction algorithm supplemented by an atmospheric catalogue which contains atmospheric correction functions, stored in look-up tables (Richter 1996). Radiative transfer calculations in ATCOR-2 use MODTRAN-5. The atmospheric database covers wide range of different weather conditions and sun angles. The atmospheric parameters include aerosol type, visibility, and water vapour. The model calculates radiometric calibration coefficients for known atmospheric parameters and known target surface reflectance and applies empirical line fit because of its adjacency effect. It also includes a fully automatic algorithm that creates masks for haze and cloud regions and removes them (ReSe 2015). ATCOR-2 algorithm works on flat terrain. ATCOR-3 is specifically designed for rugged terrain. For this purpose DEM is a mandatory input for ATCOR-3 model processing (Richter 1998). Since the study area is not undulating in nature, the ATCOR-2 model provided acceptable result. The standard calibration file was used under tropical rural atmospheric condition. The other relevant information for the model was considered from the metadata file of the sensor and from the Indian Meteorological Department (IMD) weather reports. After correcting the LISS-III image atmospherically, the corrected radiance image was converted to the Top of the Atmosphere (TOA) reflectance image. Using the Red (R) and Near Infra Red (NIR) bands, the first index SAVI was estimated using the following equation 1. This is an improved version of NDVI and considers the soil background effects on NDVI (Huete 1988).

$$\mathrm{SAVI} = \frac{\mathrm{NIR-R}}{(\mathrm{NIR+R+L})}(1+L) \qquad \text{(Huete 1988)} \qquad \mathbf{(1)}$$

where L = slope of the soil line (generally considered as 0.5).

The second index used in this study was MSAVI which is a modified version of the original SAVI. The constant L-factor of SAVI equation is replaced with variable L-factor computed using the following equation 2 (Qi et al. 1994).

$$\mathrm{L} = 1 - 2\gamma\ (NDVI\ \times WDVI) \qquad \text{(Qi } \textit{et al}\text{. 1994)} \qquad \mathbf{(2)}$$

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where γ = primary soil line parameter (generally considered as 1.06) Factor 2 is used to increase the dynamic range of L-factor. The third index applied in this study was OSAVI (equation 3) another improved version of NDVI and an optimized version of SAVI. The multiplication factor (1 + L) has been excluded because of its significant effect on the relatively large values of L (> 0.4) (Rondeaux *et al.* 1996).

$$OSAVI = \frac{NIR-R}{(NIR+R+X)} \quad \text{(Rondeaux et al. 1996)} \quad \textbf{(3)}$$

where X = parameter to minimize soil effects. A value 0.16 is considered as an optimized value.

After the estimation of these three indices, the values are regressed with the LAI measured at the sample ground locations. The best fit model was applied to estimate LAI from the index image for the whole study area.

As pointed out by Pandya *et al.* (2006), counter validation of global LAI product like MODIS LAI with respect to fine resolution satellite data product is a strong requirement for many sites. However, in comparison with the USA, Africa and Europe, this testing was not widely done in India. Therefore, this study tries to explore the response of soil adjusted vegetation indices to estimate LAI supported by ground validation in a mono-cropped mangrove vegetation dominated region. The homogeneity of crops in this region may support the upscale validation approach. The ground LAI values of the mangroves, orchards and paddy crops were estimated and regressed with the index images. Empirical equations were formed (Table 3). The best fit equation was used to estimate LAI from the LISS-III based index image.

Table 3. Estimated regression equations for the selected spectra indices

Regression Models	**Vegetation Indices**		
	SAVI	**MSAVI**	**OSAVI**
Linear	LAI = 1.531 × SAVI + 0.714 (R^2 = 0.366)	LAI = 1.891 × MSAVI + 0.079 (R^2 = 0.563)	LAI = 3.802 × OSAVI - 0.362 (R^2 = 0.839)
Logarithmic	LAI = 1.174 ln (SAVI) + 2.294 (R^2 = 0.403)	LAI = 1.433 ln (MSAVI) + 2.106 (R^2 = 0.531)	LAI = 1.632 ln (OSAVI) + 2.294 (R^2 = 0.709)
Exponential	LAI = 0.793 e 0.995 × SAVI (R^2 = 0.484)	LAI = 0.553 e 1.185 × MSAVI (R^2 = 0.691)	LAI = 0.461 e 2.245 × OSAVI (R^2 = 0.915)

MODIS LAI 4 day composite (MOD15A3) image was validated after that with respect to the LISS-III derived LAI image. Since, the spatial resolution of the MODIS LAI image is 1 km, the generated LAI image was up-scaled to 1-km resolution. Thereafter, within the study area, 30 sample points were selected and their corresponding LISS-III derived LAI and MODIS LAI values were collected. Correlation regression analysis was conducted using six models to identify the correspondence between LISS-III derived LAI and MODIS LAI products. The adopted methodology of the research work is described below (Fig. 2).

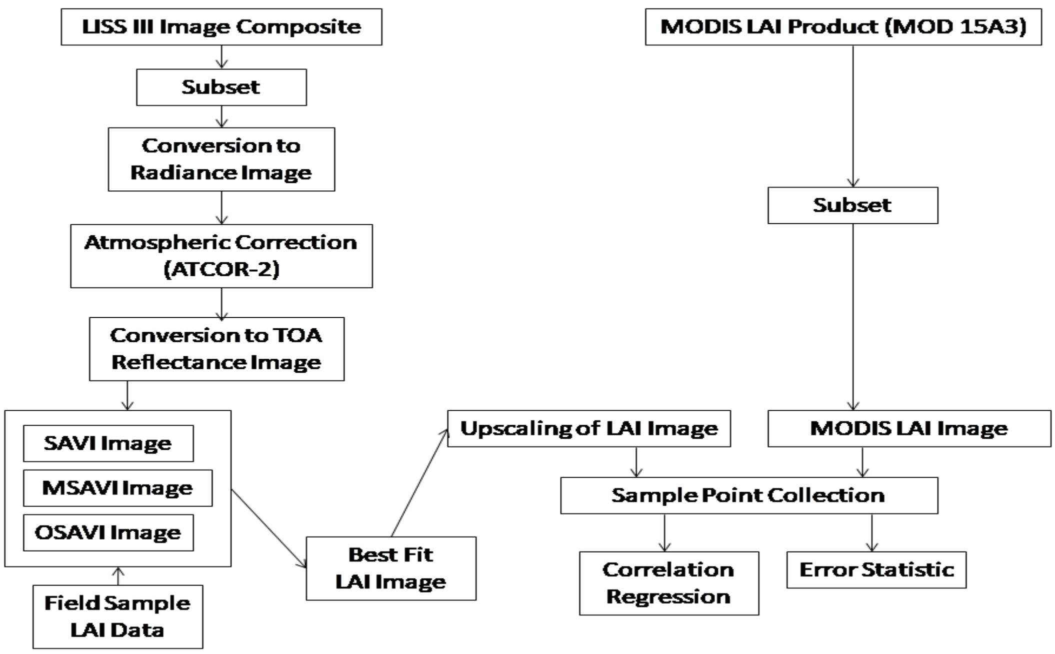

Fig. 2. Methodology.

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RESULTS AND DISCUSSION

Soil adjusted vegetation indices, i.e., SAVI, MSAVI and OSAVI applied in this study need a prior knowledge of the soil line parameters and adjusted factors suitable for operational monitoring of mangrove vegetation and paddy from the remotely sensed data. Table 4 shows the data statistics of the atmospherically-corrected index images. It is observed that for all the images, the index values are at the higher side for the agricultural crops and orchards inland and mangrove areas at the eastern, SE and western parts of the island. The lower values are observed in the non-vegetated settlement areas, palaeo-channels and other water bodies.

Table 4. Summary statistics of the applied index images

Index	Minimum	Maximum	Mean	Standard Deviation
SAVI	-0.056	1.452	1.015	0.171
MSAVI	-0.064	1.646	1.150	0.194
OSAVI	-0.038	0.968	0.677	0.114
Derived LAI	0.424	4.052	2.173	0.520

From the image it is evident that the index values decrease as soil salinity decreases. In the deltaic island like Sagar Island, high amount of salinity prevails in the boundary zones which are surrounded by salty tidal water. As one progresses inside, the salinity level in the soil decreases and causes the inner region suitable for agricultural practices (Figs. 3-5).

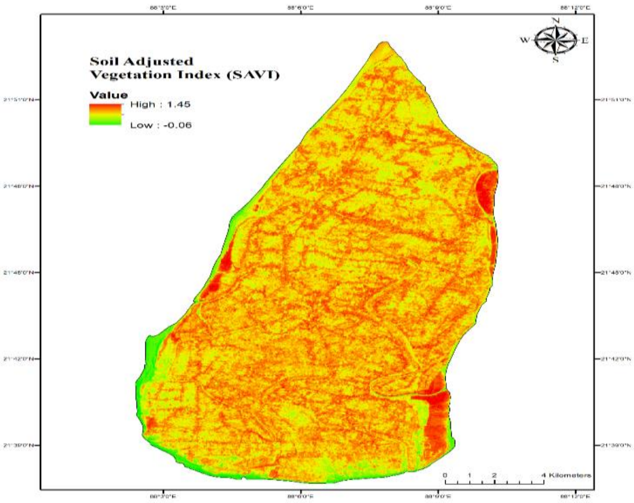

Fig. 3. Soil Adjusted Vegetation Index (SAVI).

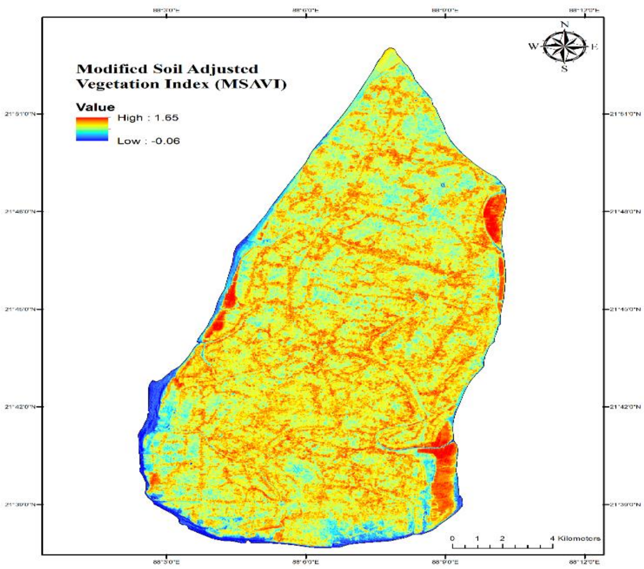

Fig. 4. Modified soil adjusted vegetation index (MSAVI).

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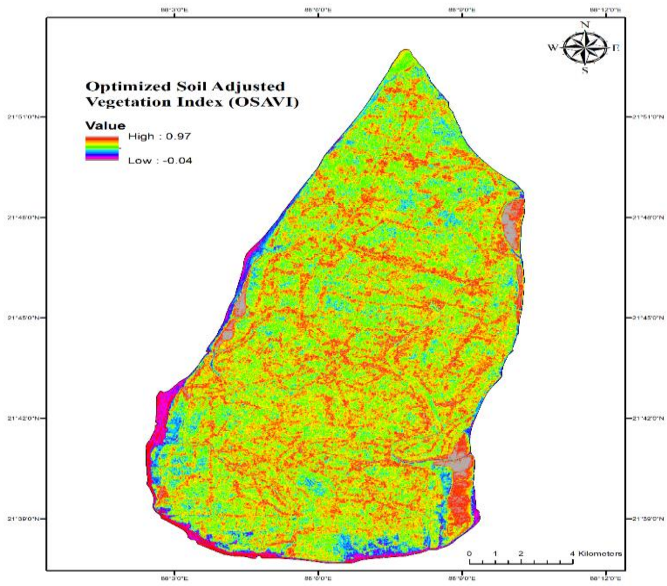

Fig. 5. Optimized soil adjusted vegetation index (OSAVI*)*.

The empirical relationship established for the index images and field collected LAI values directed towards the application of OSAVI in deriving LAI image. However, the outcomes are not based on the radiative transfer of reflectance associated with the vegetative and crop growth. Therefore, these regression equations (Table 3) may change spatio-temporally.

Several studies have already proved the applicability of SAVI to estimate LAI (Zhang & Tang 2018). Even, in tropical mangrove areas, SAVI offers equal acceptance with NDVI in estimation of LAI (George et al. 2018). The results obtained from the study depict that the use of vegetation indices for the estimation of LAI is plausible with an acceptable degree of accuracy. However, data resolution is the most important factor related to the accuracy.

Following the methodology (Fig. 2), and the best fit regression equation (Table 3), the LAI image was generated from the optimized SAVI image which yielded the best co-efficient of determination value of 0.92 out of the applied models. The LAI image (Fig. 6) shows LAI values in the range of 0.42 to 4.05. The higher LAI values are located at the eastern part of the island where the healthy mangrove vegetation persists and in the inland areas where orchards and healthy natural vegetation occur. Moderate LAI values ranging approximately from 2 to 3.5 are visible in the agricultural fields which cover the majority of the land use/cover of the island. Low LAI values are observed in the non-vegetative and un-healthy vegetative surfaces.

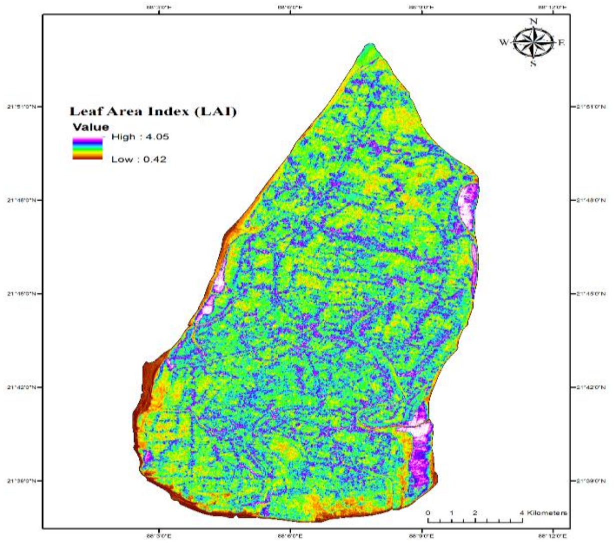

Fig. 6. LISS-III derived leaf area index (LAI).

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The coarse resolution MODIS LAI (MOD15A3) was validated with respect to LISS-III derived LAI values. Upscale validation approach based on regression analysis between MODIS LAI (dependent) and LISS-III derived LAI (independent) was adopted. It is observed that the MODIS LAI product is giving higher LAI values with respect to the LISS-III derived and field collected LAI values. This is probably the result of the aggregation effect of the surface feature reflectance. A structural dissimilarity is observed in Fig. 7. The exaggeration effect is also prominent in MODIS LAI surface in comparison with the LISS-III derived LAI surface.

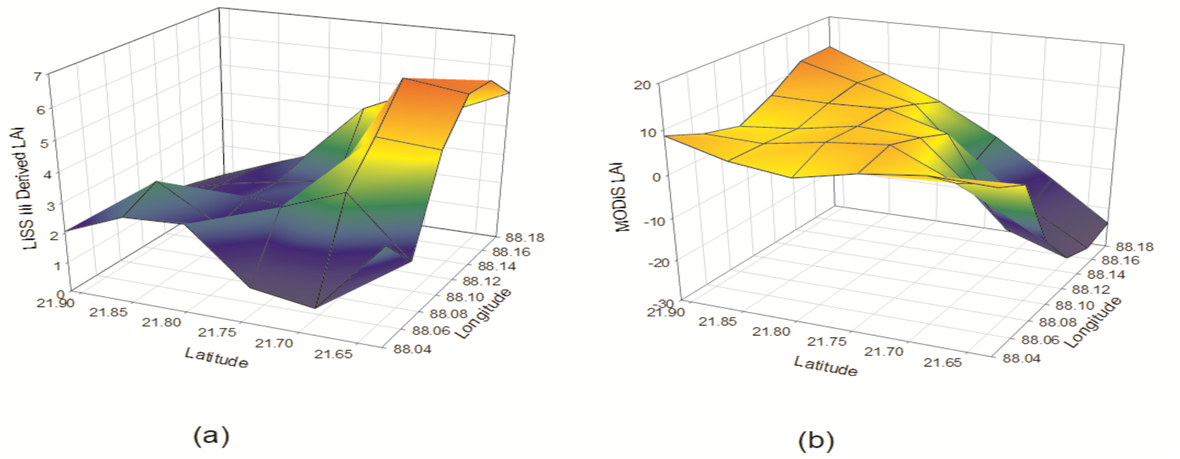

Fig. 7. 3D surface (a) LISS-III derived LAI, (b) MODIS LAI.

Based on 30 sample locations, the values of MODIS LAI and LISS-III derived LAI were regressed and developed six regression models (Fig. 8).

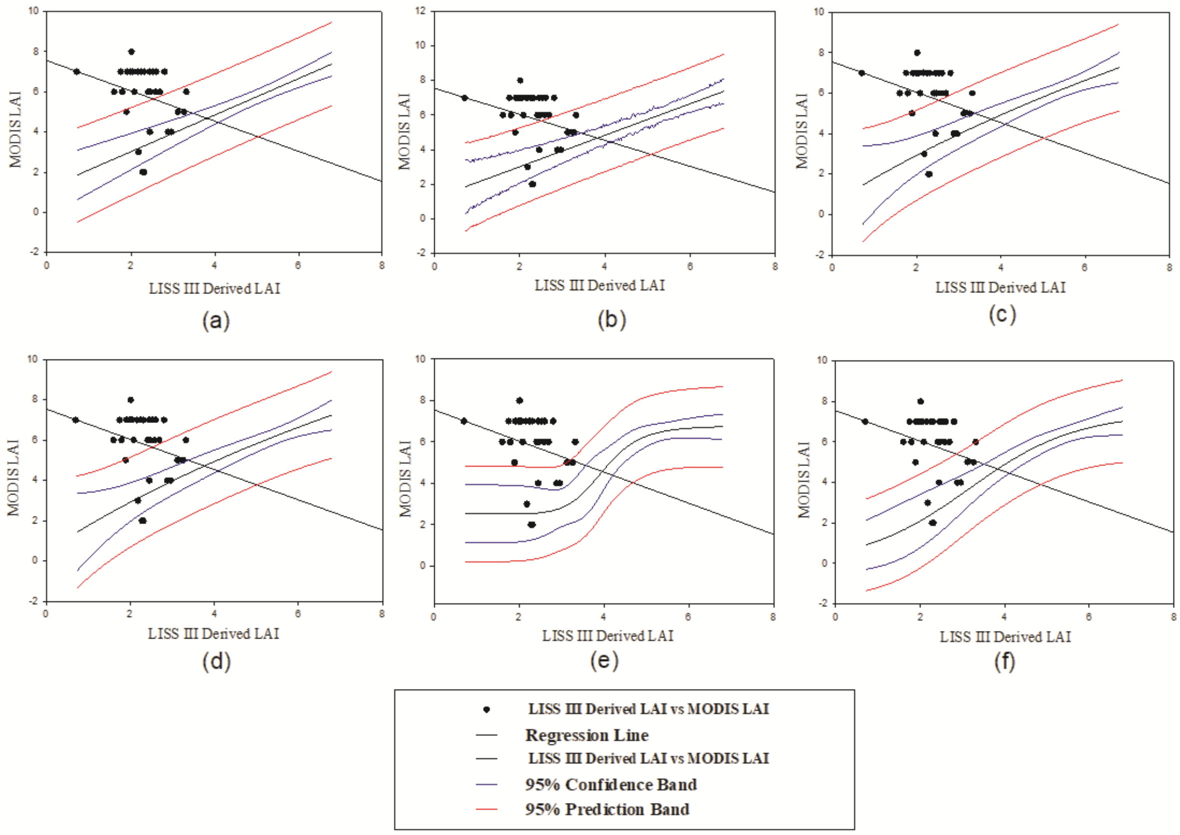

Fig. 8. Regression models showing correspondence between LISS-III derived LAI and MODIS LAI: (a) Linear, (b) Exponential, (c) Logarithmic, (d) Rational, (e) Sigmoidal, (f) Logistic.

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The standard logistic regression shows the best fit among these models ($R^2 = 0.71$, standard error of estimate = 0.89, $p < 0.0001$). The F-test for the model and t-test for the slope estimate indicate that the model is statistically significant. The equation of the logistic regression is

$$y = 2.52 + \frac{4.24}{1+(\frac{x}{3.99})^{-9.05}} \quad \textbf{(4)}$$

where x = LISS-III derived LAI and y = MODIS LAI.

The outcome of the research supports the findings of Tan *et al.* (2005), Jonckheere et al. (2004) and Pandya et al. (2006) who also identified the possible reasons for over-estimation of MODIS LAI. This may be due to spatial scaling, multiband reflectance retrieval, reflectance saturation, etc. The uncertainty of the model was also estimated and tabulated in terms of error statistic (Table 5). The uncertainty of the model can be reduced through maintaining spatial homogeneity of vegetation and crops in collecting LAI samples. However, on the other hand, imperfect atmospheric correction, geospatial errors and calibration may reduce the model accuracy.

Table 5. Error statistic

Error Statistic	Values
Co-efficient of Determination (R^2)	0.71
Mean Absolute Deviation (MAD)	3.51
Non Dimensional MAD (NDMAD)	0.56
Mean Bias Error (MBE)	-3.48
Non Dimensional MBE (NDMBE)	-0.54
Root Mean Square Error (RMSE)	3.89
Non Dimensional RMSE (NDRMSE)	0.35

CONCLUSION

In the present study, we investigated the applicability of soil adjusted vegetation indices to estimate LAI from LISS-III data in a deltaic ecosystem of Sagar Island. The focus of this study was to find out LAI quickly and directly from the multispectral satellite data for further application. For this purpose, empirical equations were established based on the field data. The approach has proven to be quite convincing when there is a lack of ground observation data. The relationship between soil-adjusted vegetation indices and LAI indicated that lush green mangroves with high green leaf density (both young and mature mangrove trees) represent healthy vegetation (high LAI), while post mature and degraded mangroves under environmental stress show an unhealthy situation (low LAI). The finding is also proved to be true for the paddy fields. In this regard, the OSAVI outperformed its siblings with better accuracy in addressing LAI conditions ($R^2 = 0.92$, $p < 0.0001$). Secondly, the study was aimed to validate MODIS LAI product with respect to the LISS-III derived LAI image. However, the model does not fit well linearly. The standard logistic regression model yielded best result with $R^2 = 0.71$, $p < 0.0001$. The error statistic list indicates the uncertainty of the model. The probable reasons may be assumed for this up-scale validation approach, are the multiband reflectance retrieval, reflectance saturation and spatial scaling. This is evident in the exaggerated values of MODIS LAI. Further scope exists to improve this empirical study using multiple regression techniques with multiple vegetation indices. However, the saturation of different vegetation indices at higher LAI is the major constraint of regression models. Secondly, the vegetation indices and LAI relationship varies both inter and intra-annually. In this regard, the three phonological stages of mangrove forests may be considered in future. Finally, it should be noted that the empirical relationship can be enhanced if the number of deltaic sites is increased, and the combination of all the above-mentioned problems and prospects can be incorporated to assess properly the health of deltaic ecosystem in the study area.

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ارزیابی اعتبار متقابل LISS-III مشتق شده از شاخص مساحت برگ در گیاهان دلتاییک

آبهیسک سانترا*، شریاشی سانترا میترا، سومان سینها

گروه مهندسی عمران، موسسه فنی هالدیا، مجموعه ICARE ، پردیس HIT ، هالدیا، ۷۲۱۶۵۷، میدناپور (E)، بنگال غربی، هندوستان

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چکیده

شاخص مساحت برگ، به عنوان یک متغیر بیوفیزیکی بدون ابعاد به عنوان یکی از مهمترین عوامل در اختصاصات ساختار سایبان در نظر گرفته می شود. این شاخص مقدار مساحت شاخ و برگ به ازای مساحت زمین را تخمین می زند و کمک می کند تا غیر مستقیم زیتوده و تعادل انرژی را ارزیابی کنیم. فنون سنجش از دور ارتباط محکمی بین خصوصیات انعکاسی گیاهان در طیف های قرمز و مادون قرمز و شاخص مساحت برگ برقرار کنیم. شمار قابل قبولی از شاخص های حا صل از تصویر گیاهان را برای تخمین شاخص مساحت برگ به طور موفقیت آمیز به کار بریم. در این مقاله ما ارتباط متقابلی بین شاخص مساحت برگ جمع آوری شده از مزرعه با سه شاخص تنظیم شده گیاهان مانند SAVI, MSAVI, OSAVI حاصل از LISS-III مشتق شده از شاخص مساحت برگ در اکوسیستم دلتاییک جزیره سگر در بنگال غربی، هندوستان برقرار می کنیم. شاخص مساحت برگ از طریق OSAVI برای کل جزیره به عنوان بهترین نتیجه حاصل از OSAVI به دست آمد (R2 = 0.92) . راه حل کلی MODIS LAI (MOD15A3) با توجه به LISS-III مشتق شده از شاخص مساحت برگ از طریق رهیافت اعتبار سنجی فرامعیاری به دست آمد. از بین شش مدل مناسب مورد استفاده رگرسیون لوجستیک بهترین ارتباط را بین دو محصول نشان داد (R2 = 0.72). عدم قطعیت این مدل نیز ارزیابی شد و دلایل احتمالی شناسایی شد.

*مولف مسئول

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