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RESEARCH PAPER

Temporal analysis of carbon sequestration pattern in evergreen vegetation using Support Vector Machine

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ABSTRACT

Support Vector Machines (SVM) are very specific class of algorithms, characterized by usage of kernels, absence of local minima, sparseness of the solution and capacity control obtained by acting on the margin, or on number of support vectors, etc. In this study the gross primary production (GPP) of evergreen tropical vegetation calculated from remote sensing data are classified using SVM. In this study, e analyzed multilayer satellite images from the vegetation (VGT) sensors on board the SPOT-4 satellite (01/2006 to 12/2009) were analysed for Cashew plantations areas of Tamilnadu, India. The temporal analysis of vegetation indices such as enhanced vegetation indices (EVI) and land surface water index (LSWI) were done and the GPP was calculated using the satellite based vegetation photosynthesis model (VPM). The enhanced vegetation index (EVI) identified subtle changes in the seasonal dynamics of leaf phenology in cashew plantation area, as supported by leaf moisture content and leaf area index. The land surface water index (LSWI) indicates that the plantation experienced water stress during the dry seasons. The VPM model which uses EVI, LSWI and site specific climate data for 2008-2009 predicted high GPP in the late wet season than in summer season. The GPP calculated from the remote sensing data are classified into three classes using SVM. The calculated GPP of di?erent months in year showed that the monthly GPP ranged from 51-128 g C/m^2. The SVM is trained to provide an output value of 0, 1 and 2 for carbon sequestration which ranged from 50-75, 76-100 and 101-125 g C/m^2, respectively. The experimental results shows that the SVM classified the carbon sequestration with an accuracy of 98.1 per cent.

Key Words : Support vector machines, Cashew, Carbon sequestration, Pattern classification, EVI, LSWI, GPP

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Global climate change is a wide spread and growing concern that has led to agreement on emission of CO_2 among different countries. Responses to this concern have focused on reducing emission of green house gases, especially carbon-di-oxide, and measuring carbon absorbed by and stored in plants, soils and oceans. One of the options for reducing the rise of green house gas concentration in the atmosphere and thus possible climate change is to increase the amount of carbon removed by and stored in plants. Forests are large reservoirs of carbon as well as potential carbon sink and sources to the atmosphere. In tropical countries like India, forest carbon sinks are believed to offset a significant portion of carbon emission associated with fossil fuel combustion. But due to large scale industrialization and increased population, the forest area is slowly declining. Perennial fruit trees like cashew, mango and guava have similar potential like forest trees to sink atmospheric carbon. Cashew is an evergreen fruit tree; it occupies nearly 40,000 ha in Tamilnadu

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and had great potential for carbon sequestration. In India, cashew is grown in seasonally moist tropical climate having a distinct dry and wet season. There is a strong seasonality of photo synthetically active radiation (PAR) usually being much larger in late wet season than in the dry season. In Cashew plantations the new leaf formation started during the end of the dry season that is during month of September which coincides with the start of winter season. In this study, we combined the analysis of satellite images with meteorological data. The objectives of this study are to estimate the seasonal dynamics of carbon sequestration in the tropical Cashew plantation area of Tamilnadu, India using vegetation photosynthetic model (VPM) and to explore the capability of SVM to classify the pattern of carbon sequestration in the cashew plantation on the basis of quantity of carbon sequestered in di?erent periods. The VPM model [Xiao *et al*., 2003) taken advantages of additional spectral bands [E.g. blue, and short wave infrared (SWIR)] that are available from advanced optical sensors. VEGETATION (VGT) sensor is the new generation optical sensor on board the SPOT-4 satellite, o?er the potential for improved characterization of vegetation at the global scale. Over the last few decades, the time-series data of the normalized di?erence vegetation index (NDVI), which is calculated as the normalized ratio between red and near-infrared (NIR) bands, have been widely used in satellite based modeling of GPP and NPP of terrestrial vegetation (Field *et al*., 1995). The advanced very high resolution radiometer (AVHRR) sensors that have red and near-infrared (NIR) bands have provided multi-decadal time series of NDVI has several limitations, including saturation in a multilayer closed canopy and sensitivity to both atmospheric aerosols and the soil background (Huete *et al*., 2002). To account for these limitations of NDVI, the enhanced vegetation index (EVI) was developed (Huete *et al*., 1997).

$$\mathbf{NDVI} = (^\circ_{nir} - ^\circ_{red}) / (^\circ_{nir} + ^\circ_{red}) \qquad (1)$$

$$\mathbf{EVI} = 2.5 \times (^\circ_{nir} - ^\circ_{red}) / (^\circ_{nir} + (6 \times ^\circ_{red} - 7.5 \times ^\circ_{blue}) + 1) \qquad (2)$$

EVI includes the blue band for atmospheric correction, which is one important feature for the study in the forest area where seasonal burning of pasture and forest takes place throughout the dry season, either for agricultural purpose (land clearing) or natural fire events. The smoke and aerosols from the biomass burning could affect NDVI substantially, irrespective of vegetation changes. The advanced optical sensors (VGT) have additional spectral bands (e.g., blue and shortwave infrared), making it possible to develop time-series data of improved vegetation indices. EVI has recently been used for the study of temperate forests (Boles *et al*., 2004) and is much less sensitive to aerosols than NDVI. As the short infrared (SWIR) spectral band is sensitive to vegetation water content and soil moisture, a combination of NIR and SWIR bands have been used to derive water sensitive vegetation indices (Ceccato *et al*., 2001) including the land surface water index (LSWI) (Xiao *et al*., 2004).

$$\mathbf{LSWI} = (^\circ_{nir} - ^\circ_{swir}) / (^\circ_{nir} + ^\circ_{swir}) \qquad (3)$$

As leaf liquid water content increases or soil moisture increases, SWIR absorption increases and SWIR reflectance decreases, resulting in an increase of LSWI value. Recent work in evergreen tropical forests has shown that LSWI is sensitive to changes in leaf water content over time (Maki *et al*., 2004).

RESEARCH METHODOLOGY

This study was conducted in cashew plantation area of Tamilnadu, India. The study area lies between $11^0 15'$ N to $11^0 43'$ N latitude and $79^0 16'$ E to $79^o 44'$ E longitude and covers total area of 40,000ha. The annual rainfall ranges from 750 mm to 1100 mm with an average of 900 mm. October to December is the peak of wet season with mean monthly rainfall of 300 mm. The study area has two rainfall regimes that are wet and dry seasons. The wet season stretches from October to January and the dry season ranges from February to September. The average mean temperature is 32^0C. The mean minimum temperature is 24.2^0C. Mean maximum temperature is 38^0C. The mean annual solar net radiation is 16.9MJm^{-2} day^{-1}, where as the relative air humidity ranges from 80 to 90 with an average of 85. The soil in the study area is characterized by neutral, deep, strongly weathered, moderately well drained. Inceptisols and Alfisoil are the dominant soil types in the study area. The elevation of the study area ranges from 48 to 55 MSL.

The VPM model developed by Xiao *et al*. (2003) was used for calculating carbon sequestration in this study area. The VPM model has three sets of parameters to be estimated. In this study, we used a E_0 value of 0.045 µmol CO_2/µmol PAR, by following Xiao *et al*. (2005). The second parameter set is for calculation of T_{scalar} (7). For tropical forest, we used a minimum temperature (T_{min}) of 2^oC, optimum temperature (T_{opt}) of 28^0C, and maximum temperature (T_{max}) of 48^0C, as implemented in the process-based Terrestrial Ecosystem Model (Raich *et al*., 1991; Tian *et al*., 1998). The third parameter set is for calculation of W_{scalar} (8). Estimation of site specific $LSWI_{max}$ is dependent upon the optical sensor and the time series of image data. The maximum LSWI value within the plant-growing season is selected as an estimate of $LSWI_{max}$ (Xiao *et al*., 2004). Field measurement was conducted in order to collect data such as leaf area index, leaf moisture content. Photosynthetic photon flux density is measured using portable photosynthetic system Li-6400. Temporal variability analysis is conducted to assess the temporal dynamics of carbon sequestration in the plantation area.

10-day composite images from the VEGETATION sensor:

The VEGETATION (VGT) sensor on board the SPOT-4 satellite is one of a new generation of space-borne optical sensors that were designed for the observation of vegetation and land surfaces. The VGT instrument has four spectral bands: blue (430-470 nm), red (610-680 nm), near-infrared (NIR, 780-890 nm), and shortwave infrared (SWIR, 1580- 1750 nm). The blue band is primarily used for atmospheric correction. The SWIR band is sensitive to soil moisture, vegetation cover, and leaf moisture content. Unlike scanner sensors (e.g., AVHRR, MODIS), the VGT instrument uses the linear-array technology (push-broom), and thus produce high-quality images at moderate resolution (1 km) with greatly reduced distortion. Since its launch in March 1998, the VGT instrument has acquired daily images at 1-km spatial resolution for the globe. The VEGETATION Programme produces three standard VGT products: VGT - P (physical product), VGT-S1 (daily synthesis product) and VGT-S10 (10-day synthesis product). The spectral bands in the VGT-S1 products are estimates of ground surface reflectance, as atmospheric correction of ozone, aerosols and water vapor have been applied to the VGT-P images using the Simplified Method for Atmospheric Correction (SMAC) algorithm (Rahman and Dedieu, 1994). VGT-S10 data are generated by selecting the VGT-S1 pixels that have the maximum Normalized Difference Vegetation Index (NDVI) values within a 10-day period. The maximum NDVI value composite (MVC) approach helps to minimize the efects of cloud cover and variability in atmospheric optical depth. There are three 10-day composites for 1 month: day 1-10, day 11-20, and day 21 to the last day of the months. The VGT-S10 products are freely available to the public (http://free.vgt.vito.be). We have acquired the VGT-S10 data over the period of January 1-10, 2006 to December 21-31, 2009 for the globe. We calculated NDVI, EVI and LSWI, using the surface reflectance of blue (ρ_{blue}), red (ρ_{red}), nir (ρ_{nir}), and swir (ρ_{swir}) bands from the standard VGT-S10 data. The preprocessing and calculation of vegetation indices from the VGT-S10 data were done as described by Xiao *et al*., 2003. Cloudy observations in a time series of vegetation indices were gap-filled using a simple gap-filling method and the cloud quality flag in the VGT-S10 surface reflectance files (Xiao *et al*., 2003). In this study, we selected 3 × 3 pixels (approximately $3 \times 3km^2$) that covered the Vridhachalam meteorological station for feature extraction and calculated the GPP. Thus calculated GPP is classified using support vector machine.

Support vector machine (SVM) for classification:

Support Vector Machine (SVM) (Christopher, 1998; Vapnik, 1998) is based on the principle of structural risk minimization (SRM). Like RBFNN, support vector machines can be used for pattern classification and nonlinear regression problems (Geetha *et al*., 2009). SVM constructs a linear model to estimate the decision function using non-linear class boundaries based on support vectors (Fig. B). If the data are linearly separated, SVM trains linear machines for an optimal hyper plane that separates the data without error and into the maximum distance between the hyper plane and the closest training points. The training points that are closest to the optimal separating hyper plane are called support vectors. Fig. A shows the architecture of the SVM.

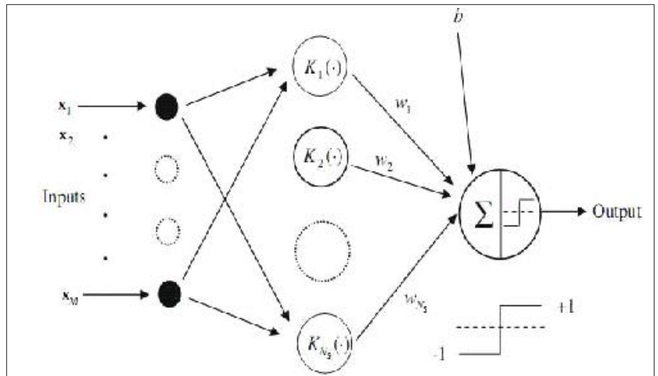

Fig. A : Architecture of the SVM (Ns is the number of support vectors)

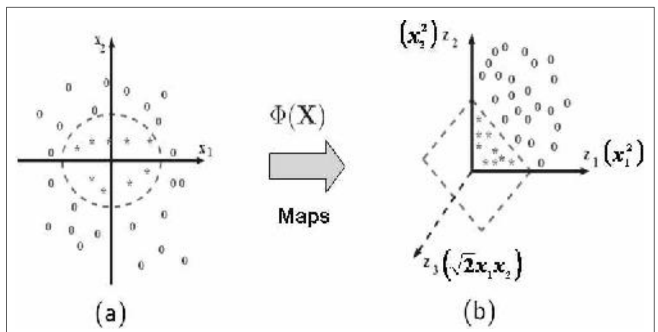

Fig. B : An example for SVM kernel function _(x) maps 2-Dimensional input space to higher 3- Dimensional feature space. (a) Nonlinear problem. (b) Linear problem

RESULTS AND REMONSTRATION

The seasonal dynamics of EVI as shown in Fig. 1 is likely driven by a change in the leaf area index as the canopy of seasonally moist tropical cashew plantation had varying LAI as shown in Fig. 2 over seasons. We hypothesize that the seasonal distribution of EVI in a year may be attributed to both leaf fall of old leaves and emergence of new leaves resulting in dynamic changes in proportion of young and old leaves within a vegetation canopy over seasons. In general, the old leaves have less chlorophyll and water content but more structured material (Eg. lignin, cellulose) in comparison to young leaves which could lead to significant changes in absorbance, transmittance and reflectance of leaves as the aging process of leaves progress.

The EVI continued to maintain higher value even up to

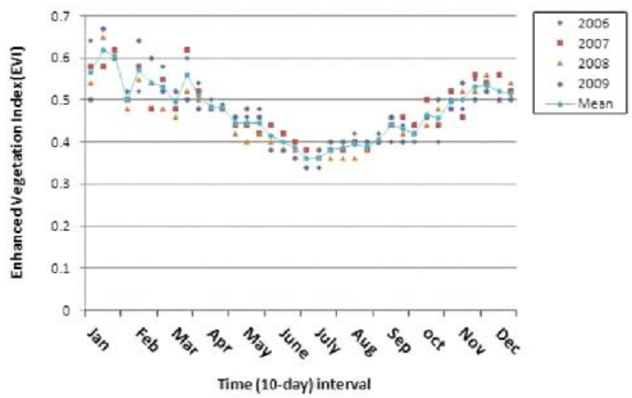

Fig. 1 : Seasonal dynamics of enhanced vegetation index (EVI)

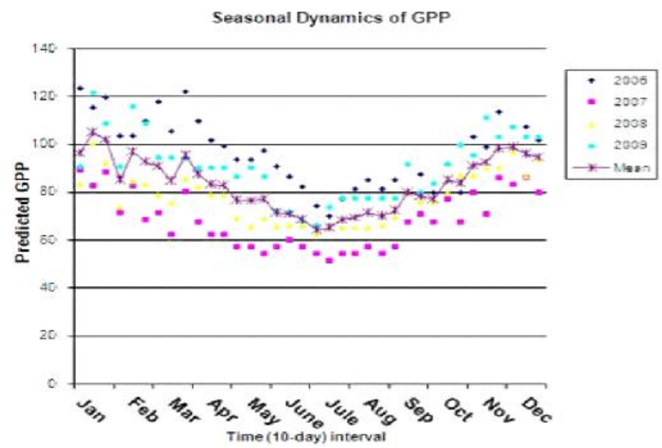

Fig. 3 : Seasonal dynamics of LSWI

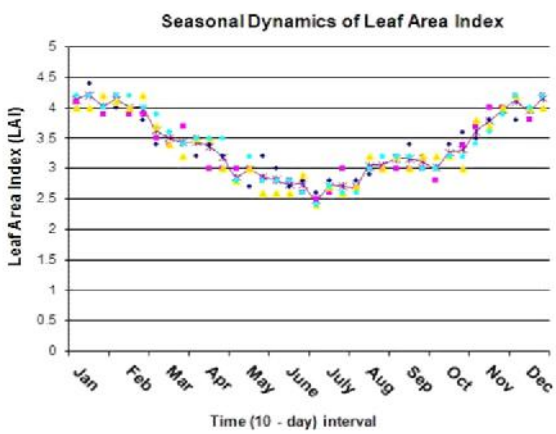

Fig. 2 : Seasonal dynamics of leaf area index (LAI)

February which may be attributed to continued emergence of new flushes in the winter season. The peak EVI values had the time lag of two months (January-February). The observed decrease of EVI in the peak dry season (May-June) could be largely attributed to aging process of leaves, including increase of both leaf thickness and the non-photosynthetic vegetation (NPV) component. This fact is supported by the field data. Field data collected at the experimental site showed that new leaf flush emergence starts during the end of September and continued up to January. The decrease in EVI from April to September may be attributed to both leaf age (older leaves) and epiphyll cover (Huete *et al*., 2003).

Young leaves have higher photosynthetic capacity than older leaves. We used time series data (2006-2009) of LSWI to assess the status of leaf canopy water content of seasonally moist tropical Cashew plantation. LSWI values were generally higher in the wet season than in the dry season as shown in Fig. 3. The seasonal dynamics of LSWI from 2006-2009 were positively correlated with that of leaf moisture content. The observed evapotranspiration data from the metrological research station were also higher in dry season than in the wet season as shown in Fig. 4. The high LSWI values in the month of December-February might be due to high proportion of young leaves and more leaf water content as indicated by leaf moisture data and seasonal dynamics of EVI. Usually young leaves have more water content than old leaves. The seasonal dynamics of LSWI shown that water stress exist in the experimental area during the dry season from 2006-2009.

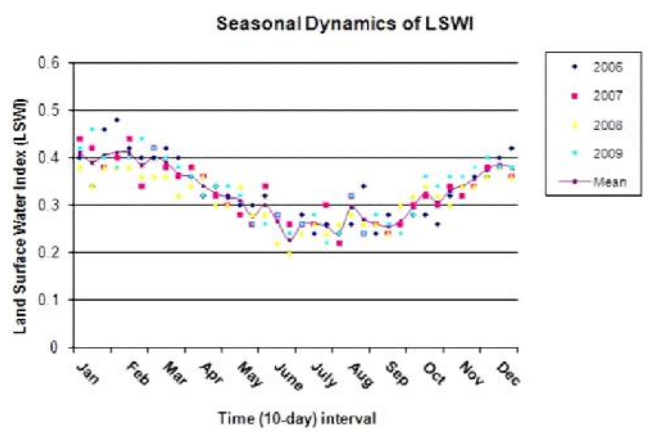

Fig. 4 : Seasonal dynamics of global primary productivity (GPP)

Calculation of GPP in VPM model using 10 day VGT composites:

We used the VPM to estimate the GPP using LSWI, EVI and site specific climate (air temperature). As photosynthesis is closely coupled with water flux (we used observed water flux evapotranspiration) from the nearest metrological station in the experimental site to evaluate the performance of the VPM model as shown in Fig. 5. The seasonal dynamics of predicted GPP agreed seasonably well with of observed evapotranspiration. The VPM model predicts high GPP in the late wet season, as compared to dry season. For instance, the monthly GPP_{pred} was 121.29 g C/m^2 in January 2009 (wet season) but 65.91 g C/m^2 in June 2009 (dry season). Fig. 4 shows that the relatively low GPP_{pred} in the dry season can be attributed to a number of factors. First the moisture stress in soil and maturity of leaves, secondly the averaged EVI value was lower (0.42) in late dry season (July-September) than in wet season (0.55) as shown in Fig. 3. As EVI seasonal dynamics related to leaf phenology (leaf fall, leaf emergence) at the canopy level. This suggests that leaf phenology could play an important role in the GPP calculation of seasonally moist tropical cashew plantation. The annual sum of predicted GPP in cashew plantation is (11967.811 g C/m^2 / year).

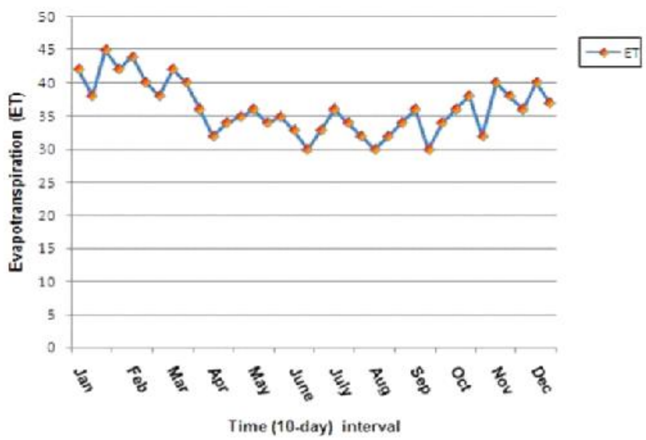

Fig. 5 : Seasonal dynamics of evaoptranspiration (ET)

Training and testing of SVM:

The nine attributes derived from remote sensing image and climate data are used to train the support vector machine. Training data include the class label so a total of 10 attributes is fed to the classifier while the test data had only nine attributes excluding the class attribute. SVMTorch, a freely available C++ based object-oriented machine learning library is used for training and testing the model.

The calculated GPP of different months in a year showed that the monthly GPP ranged from 51-128 g C/m^2. The SVM is trained to output the class labels 0, 1 and 2 for carbon sequestration which ranged from 50-75 g C/m^2, 76-100 g C/m^2 and 101-125 g C/m^2, respectively. Fig. 6 shows the performance of SVM for varying number of training samples. In all the experiments 36 samples are used for testing. Increasing in the number of samples progressively increased the performance of SVM up to 144, beyond that the curve becomes flat which indicates that 144 samples are required to obtain the optimum performance. In order to compare the performance of the four di?erent kernels *viz.*, linear, polynomial, Gaussian and sigmoid, each kernel is used in SVM and it is trained with 144 samples and tested with 36 samples. Among the four kernels, Gaussian kernel showed highest accuracy as compared to other kernels

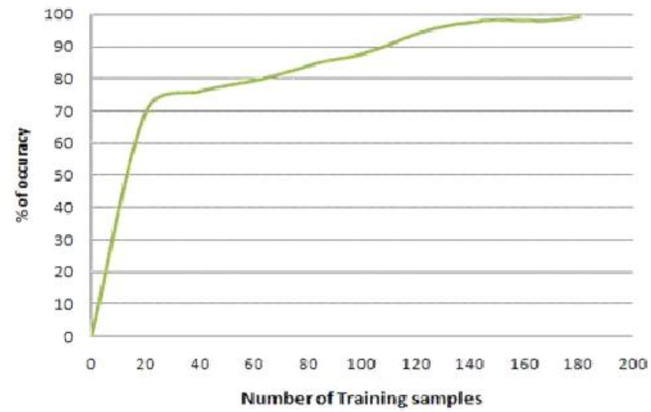

Fig. 6 : Performance curve

as shown in Fig. 7 Table 2 shows the confusion matrix of classification. Confusion matrix shows that 2.6 per cent of samples in class-0 is classified as class-2 and 0.2 per cent of samples in class-0 is classed as class-1 by the support vector machine. Over all accuracy of SVM is calculated using the confusion matrix. The data from three different classes are applied in confusion matrix so as to calculate the accuracy of SVM.

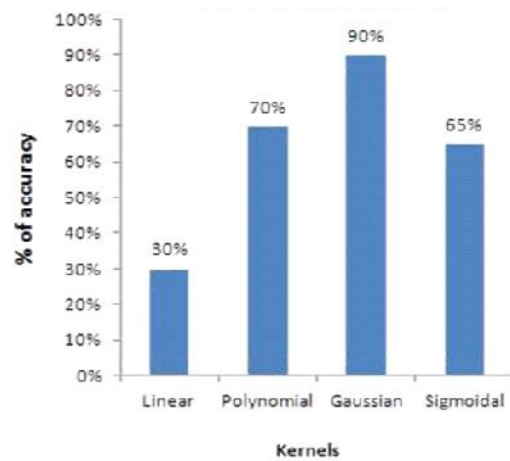

Fig. 7 : Performance for classification in different kernels

Table 1 : Confusion matrix of classification (in %)

Classes	Class 0	Class 1	Class 2
Class 0	97.2	0.2	2.6
Class 1	0	98.3	1.7
Class 2	1.0	0.2	98.8

Conclusion:

In this study we evaluated the seasonal dynamics of vegetation indices (EVI, LSWI and NDVI) from VGT sensor for a seasonally moist tropical cashew plantation in Tamilnadu, India. Strong seasonal dynamics of EVI, and LSWI from VGT was observed at the experimental site. In this study, our explanation for the seasonal dynamics of EVI, LSWI focus primarily on leaf phenology, leaf age, and leaf moisture content. As compared to other production e?ciency model (PEM) that are based on NDVI-LAI-FAPAR relationship , the VPM model implements three hypothesis and alternate approaches in its model formulation (Xiao *et al*., 2004).

The first hypothesis is the conceptual partitioning of PAV and NPV. We assumed that the advanced vegetation indices (Eg. EVI) are capable of tracking subtle changes in PAV and NPV at leaf level, in addition to canopy level structured changes (LAI, plant area index) of forest are usually has little changes over plant growing seasons. In the second hypothesis is moisture content of leaf and canopy level, we assume that advanced vegetation indices (Eg. LSWI) are capable of tracking changes in leaf water content over the plant growing season. The third hypothesis is leaf phenology (leaf fall, leaf emergence) and we assumed that improved vegetation indices (Eg. EVI and LSWI) from advanced optical sensors are capable of detecting subtle changes in leaf optical properties associated with changes in anatomical and biochemical and biophysical properties at di?erent leaf ages. The results of the study are likely to have significant implications to remote sensing analysis of seasonally moist tropical vegetation, carbon cycle and climate modeling. This study has also explored the potential of SVM to predict and classify the carbon sequestration pattern in tropical evergreen vegetation. The SVM classifies the Carbon sequestration with an accuracy of 98.1 per cent.

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