INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **28**: 1807–1819 (2008)
Published online 13 February 2008 in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/joc.1662

Effects of precipitation, temperature and topographic parameters on evergreen vegetation greenery in the Western Ghats, India

V. Krishna Prasad,[a]* K. V. S. Badarinath[b] and Anuradha Eaturu[c]
[a] *Agroecosystem Management Program, The Ohio State University, USA*
[b] *National Remote Sensing Agency, Department of Space,- Government of India, India*
[c] *Department of Mathematics, Kent State University, USA*

ABSTRACT: Bi-weekly National Oceanic and Atmospheric Administration-advanced very high-resolution radiometer (NOAA-AVHRR) satellite data covering a fourteen-year time period (1990–2003) were used to examine spatial patterns in the normalized difference vegetation index (NDVI) and their relationships with environmental variables covering tropical evergreen forests of the Western Ghats, India. NDVI values and corresponding environmental variables were extracted from 23 different forested sites using the NOAA-AVHRR global inventory monitoring and modelling studies (GIMMS) dataset. We specifically used the partial least square (PLS) multivariate regression technique that combines features from principal component analysis and multiple regression to link spatial patterns in NDVI with the environmental variables. PLS regression analysis suggested the two-component model to be the best model, explaining nearly 71% of the variance in the NDVI datasets with relatively good R^2 value of 0.78 and a predicted R^2 value of 0.74. The most important positive predictors for NDVI included Riva's continentality index, precipitation indicators summed over different quarters, average precipitation and elevation. Also, the results from PLS regression clearly suggested that bio-climatic indicators that relied only on precipitation parameters had much more positive influence than indicators that combined both temperature and precipitation together. These results highlight the climatic controls of vegetation vigor in evergreen forests and have implications for monitoring bio-spheric activity, developing prognostic phenology models and deriving land cover maps in the Western Ghats region of India. Copyright © 2008 Royal Meteorological Society

KEY WORDS phenology; vegetation vigor; satellite data; PLS regression

Received 28 March 2007; Accepted 10 November 2007

1. Introduction

Phenology represents the seasonal cycle of vegetation functioning and it reflects physiological and morphological adaptations of species and plant communities in utilizing resources (Kemp and Gardetto, 1982). Use of remote-sensing data for inferring phenological characteristics of vegetation is becoming popular due to its multi-temporal, multi-spectral, synoptic and repetitive coverage capabilities. Several studies utilized information from vegetation indices to capture phenology changes (Justice *et al*., 1986; Myneni *et al*., 1997; Suzuki *et al*., 2000). One of the important indicators of vegetation presence, abundance and vigor is the Normalized Difference Vegetation Index (NDVI). NDVI makes use of bio-physical interactions whereby healthy green plant canopies absorb much of the radiation in the visible wavelengths and are highly reflective in the infrared (Jensen, 2000). The NDVI computed as (near-infrared − red/near-infrared + red channels) is the most commonly used index for large-area phenology studies (Goward *et al*., 1985; Tucker and Sellers, 1986). NDVI is more strongly coupled to red-band reflectance, while the other indices are more coupled to near-infrared reflectance. NDVI thus, seems to be well suited for studies concerned with the photosynthetic capacity of vegetation cover (fraction of Photosynthetic Active Radiation (fPAR)and fractional green cover), while Soil Adjusted Vegetation Index (SAVI) and Soil adjusted Atmospherically Resistant Vegetation Index (SARVI) are suitable for studies that are concerned with structural canopy parameters (LAI as Leaf Area Index (LAI), biomass) that are more apparent in the near-infrared reflectance (Huete, 1988; Reed *et al*., 2003). The National Oceanic and Atmospheric Administration's (NOAA) advanced very high-resolution radiometer (AVHRR), sensor has a near-daily repeat cycle of the Earth and a 1-km spatial resolution. Both the temporal density of the data and the moderate spatial resolution make this sensor well suited for studying large-area phenology. Further, AVHRR-NDVI data are readily available in a consistently processed database from 1982 to the present at an 8-km re-sampling grid covering the globe.

Climate influences of satellite measures of vegetation and the prospects for using climate–vegetation satellite

* Correspondence to: V. Krishna Prasad, 201 Thorne Hall, 1680 Madison Avenue, Agroecosystem Management Program, The Ohio State University, Wooster, OHIO, USA. E-mail: krisvkp@yahoo.com

Copyright © 2008 Royal Meteorological Society

data relationship for understanding phenological changes has been attempted by several researchers (Farrar *et al.*, 1994; Schultz and Halpert, 1995; Ichii *et al.*, 2002). It is well established that there is a close relationship between vegetation distribution patterns and climatic parameters on a global scale (Borchert, 1998), and the major vegetation types of the world have been well correlated with minimum temperature resistance, growing season duration and temperature, and the hydrological budget (Woodward and McKee, 1991). Most importantly, the ability of the NDVI to monitor intra-annual and inter-annual spatial variability of vegetation provides a basis for spatio-temporal phenological investigations (Schwartz and Reed, 1999; Nightingale and Phinn, 2003). For example, Malingreau (1986) described the relationship between the NDVI time series and the phenological characteristics of vegetation in some areas of Asia. Malo and Nicholson (1990) used NDVI to examine relationships between rainfall and vegetation dynamics in the Sahel. Myneni *et al.* (1997) found NDVI anomalies over regions of arid and semi-arid land to be correlated with tropical Pacific sea surface temperature. Kogan (1997) confirmed the usefulness of the NDVI-based Vegetation Condition Index (VCI) to assess plant, water and temperature related vegetation stress on several continents. Moulin *et al.* (1997) visualized the phenological evolution (dormancy, growth and vegetation) of global vegetation by analysing the seasonal variation of the NDVI. Potter and Brooks (1998) quantitatively demonstrated a strong predictive relation between climate and seasonal trends in NDVI on a global level. Suzuki and Masuda (2004) showed that both temperature and precipitation have a relationship to the high NDVI vegetation in the case of arid areas. Also, Suzuki *et al.* (2006) used NDVI climate relationships to delineate wetness dominant and warmth dominant vegetation distribution types at a global scale.

Further, as climatology has a specific role in explaining phenology patterns, several remote-sensing studies demonstrated these relationships on regional and continental scales (Justice *et al.*, 1986; Townshend and Justice, 1986; Goward, 1989; Malo and Nicholson, 1990; Davenport and Nicholson, 1993; Nicholson and Farrar, 1994; Myneni *et al.*, 1997; Juarez and Liu, 2001; Gensuo *et al.*, 2002; Wang *et al.*, 2003; David and Phillip, 2004). These studies and several others, conclude that there is a strong relationship between climate variability and fluctuations in satellite-derived vegetation indices at local, regional and continental scales (Justice *et al.*, 1986; Tateishi and Kajiwara, 1992; Myneni *et al.*, 1997; Paruelo and Lauenroth, 1998; Schwartz and Reed, 1999; Ichii *et al.*, 2002; Nemani *et al.*, 2003; Jolly and Running, 2004; Tateishi and Ebata, 2004; Zhou *et al.*, 2003; Karlsen *et al.*, 2006; Suzuki *et al.*, 2006).

Although, several of the above studies clearly established strong relationships between NDVI representing plant phenological variables and climatic parameters, some of the earlier studies clearly pointed out that these relationships are ecosystem-dependent and can be highly site-specific (Nicholson and Farrar, 1994; White *et al.*, 1997; Chen *et al.*, 2001; Reed *et al.*, 2003). The degree to which important climatic controls, such as temperature and precipitation affect plant phenology, and thereby NDVI variations have been shown to vary with location (Jolly and Running, 2004). In particular, the rules that predict the phenology in temperate regions do not apply to tropical regions. For example, several factors such as changes in water level stored by plants (Reich and Borchert, 1984), seasonal variations in rainfall (Opler *et al.*, 1976), changes in seasonal temperature (Ashton *et al.*, 1988), photoperiod (van Schaik *et al.*, 1993), radiation (Wright and van Schaik, 1994) or sporadic climatic events (Sakai, 2001) have been proposed as the main causes of leaf production or leaf abscission in tropical forest plants. Also, bridging the gap from individual forest type phenology models to regional ecosystem phenology requires assessing the effectiveness of ecosystem-specific phenological models developed at a local scale. In such a context, addressing the spatial controls of phenological changes at local scale gains significance. In the Indian region, more than 16 different forest type formations have been reported (Champion and Seth, 1968). In particular, relatively few studies have demonstrated the usefulness of satellite bio-climatology in the tropical forests of Western Ghats region, India. The Western Ghats are spread over an area of 160 000 km^2 and contain eight national parks and 39 wildlife sanctuaries. The mountain ranges of the Western Ghats in south India present an interesting combination of meteorological and physical characteristics. They represent unique bio-climatic context involving monsoon-influenced climate as well as orography induced elevation regimes. The north–south running bio-geographical system exhibits contrasting vegetation formations, with unique taxonomic hierarchies, remnant ecosystems and strong endemic associations. Spatial variation in climate and topography in the Western Ghats region have been strongly related to latitudinal gradients in forest cover types and richness.

In this study, we examine the spatial patterns of vegetation vigor (NDVI) as they relate to different meteorological as well as topographic parameters in the Western Ghats region. Also, the goal of this study is to link and relate the key bio-climatic indices capable of addressing vegetation vigor and its variability in the study region. For addressing these objectives, we used satellite remote-sensing data from NOAA-AVHRR in conjunction with meteorological datasets in a robust statistical framework. The results from this study are expected to provide useful information relating to climatic controls of vegetation vigor in the tropical evergreen forests of the study area.

2. Study area

The Western Ghats of India are recognized as one of the world's bio-diversity hotspots (Myers *et al.*, 2000). They stretch from a 1500 km-long escarpment parallel to the southwestern coast of the Indian peninsula. Nearly 63% of the evergreen tree species are endemic to this

Copyright © 2008 Royal Meteorological Society

region (Ramesh and Pascal, 1991). The Western Ghats form an unbroken relief dominating the west coast of the Indian peninsula, for almost 600 km, extending between north latitudes of 8 and 21°. The Western Ghats' ranges form a barrier to the monsoon winds originating in the Indian Ocean and moving northeast. Hence, rainfall in the region is very heavy during the southwest monsoon, which lasts between June and October. Annual rainfall exceeds 6000 mm all along the escarpments, with the wettest areas in the region recording about 7800 mm. Rainfall magnitude decreases steadily towards the east, to a minimum of 1200 mm in areas bordering the Ghats. More than 90% of the rainfall occurs during the four monsoon months, with an average number of 120–140 rainy days per year. During the monsoon, a major portion of rainfall is contributed by four to five spells each lasting 8–10 days. During such spells, daily values are very high. Geologically, the study area consists of Precambrian formations with gneiss and intrusive granites forming the important rock types. Soils in the surface layer are usually sandy loams, characterized by very high infiltration rates, even on the rounded crests of the hills. Climatic characteristics in the Western Ghats region have been extensively described in Gunnell (1997). Forest vegetation in the Western Ghats can be classified into three types: (1) thick evergreen to semi-evergreen forests occupying vast stretches of the steep slopes (2) the evergreen montane forests confined to the valleys and locally called Sholas and (3) pastures, covering extensive areas on the rounded crests of the escarpment of the Ghats. Also, mostly, the western side of the Ghats supports wet evergreen forests, whereas the eastern side supports deciduous forest pockets, with the exception of a belt of dry evergreen forests in the south (Pascal, 1992). Detailed floristic maps have been prepared by the French Institute of Pondicherry, India, in collaboration with local forest departments (Pascal, 1982a,b). The study area location map is shown in Figure 1 and the dominant floristic composition along the altitudinal ranges is summarized in Table I.

3. Data and methods

3.1. GIMMS NDVI data

We used NDVI data from the Global Inventory Monitoring and Modelling Studies (GIMMS) group, derived from the NOAA/AVHRR land data set, at a spatial resolution of 8×8 km^2 (Tucker *et al.*, 2004, 2005). The GIMMS NDVI data are composited bi-weekly, with the first 15 days of the month compiled in one file and the remaining days of the same month in another. These datasets are available for a 22-year period spanning from 1981 to 2003. The GIMMS data are available to the scientific community (e.g. through the Global Land Cover Facility, http://glcf.umiacs.umd.edu). There are several advantages to using GIMMS-composited NDVI datasets, including the reduced effects of variable cloud cover, solar and viewing geometry, orbital drift, sensor degradation and the emission of volcanic aerosols that attenuate

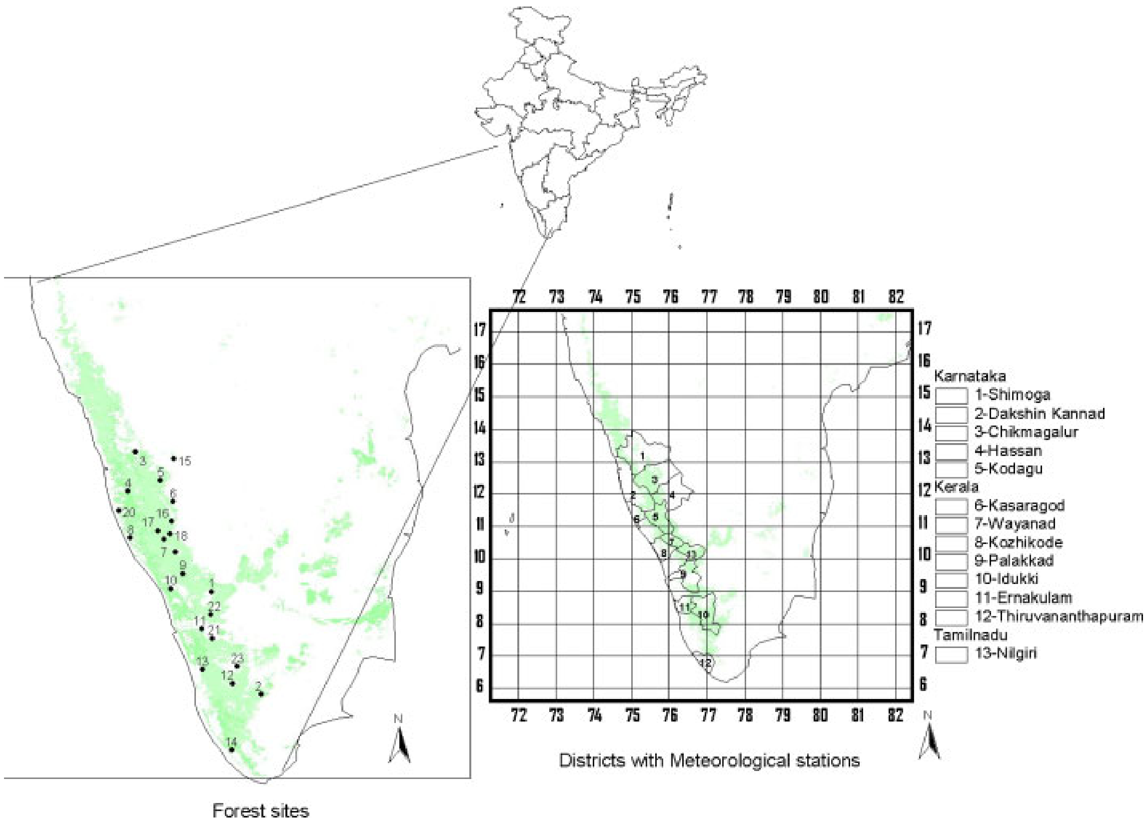

Figure 1. The forested areas are shown in gray color' in the print version. This figure is available in colour online at www.interscience.wiley.com/ijoc

Copyright © 2008 Royal Meteorological Society

DOI: 10.1002/joc

Table I. Evergreen forests of the Western Ghats and their ecological conditions.

Elevation (m)	Species composition	Latitude	Total rainfall (mm/yr^{-1})	Temperature (mean °C)	Dry season (months)
Low 600–700	*Dipterocarpus bourdillonii* *Dipterocarpus indicus* *Anacolosa densiflora*	8°50′–10°30′	2000–5000	>15	2–4
Medium 700–1400	*Cullenia exarillata* *Mesua ferrea* *Palaquium ellipticum*	8°20′–11°55′	3000–5000	9–18	2–5
High 1250–1800	*Schefflera spp.* *Meliosma arnottiana* *Gordonia obtusa*	10°10′–10°90′	≥2000	9–13	3–6

Table II. Locations of 23 different forest sites, Western Ghats, India.

Site	°Lat	°Long	Location	District
1	8.29	77.15	Agasthyamalai	Thiruvananthapuram
2	8.48	77.12	Idukki wildlife sanctuary	Idukki
3	8.49	77.3	Yeru R.F	Kamarajar
4	8.49	77.11	Pongu Malai	Idukki
5	10.07	76.48	Mallayattur	Ernakulam
6	10.25	76.52	Varagalair, Palghat	Palghat
7	10.31	76.2	Patticard RF	Kodagu
8	11.30	76.1	Lakkidi	Waynad
9	11.32	76.1	Pukkot	Palakkad
10	11.42	76.18	Alatur	Palghat
11	11.43	76.45	Mudumalai	Nilgiris
12	11.50	75.47	Amjilha	Kozhikode
13	12.13	75.4	Kuliyangad	Dakshin Kannada
14	12.22	75.3	Tala Cauvery	Kodagu
15	12.30	75.39	Uppangala	Kodagu
16	12.30	75.52	Magador	Kodagu
17	12.35	75.27	Dodtotta	Dakshin Kannada
18	12.50	75.5	Brahma-giri-makut	Coorg/Kodagu
19	12.60	75.45	Memonkolli	Kasargod
20	12.60	75.46	Jamedar kallu	Hassan
21	13.19	75.15	Kundremukh national park	Chikmagalur
22	13.38	75.48	Santhalli	Chikmagalur
23	14.00	74.45	Shimoga	Shimoga

the reflectance spectra (Zhou *et al*., 2001; Tucker *et al*., 2004). For example, Slayback *et al*. (2003) used four different processed and corrected AVHRR-NDVI datasets to evaluate the effects of NDVI trends unrelated to vegetation activity, and found that the GIMMS dataset can be used to identify long-term trends in vegetation activity (Goetz *et al*., 2006). Detailed calibrations on this NDVI dataset can be found in Los (1998) and Tucker *et al*. (2004). The maximum NDVI value composite (MVC) (a maximum daily NDVI value in each 15 days) employed in generating GIMMS datasets, minimizes atmospheric effects, scan angle effects, cloud contamination and solar zenith angle effects (Holben, 1986).

Using these datasets, we selected NDVI values corresponding to 23 different latitudinal gradients representing different forest communities (Figure 1). We selected the bi-monthly NDVI values covering three pixel neighbourhood locations at each site (Table II) and then averaged the values over a fourteen-year time period (1990–2003). The 3×3 pixel neighbourhood criteria was used to avoid contamination of NDVI pixels due to land cover heterogeneity such as from lakes, human interference, altitude, etc. The NDVI images for different seasons are shown in Figure 2 with site-specific variations in Figure 3. The fifteen-day averaged climatic data corresponding to these locations and years (1990–2003) have been obtained from the nearest meteorological stations, district census books and from Parthasarathy *et al*. (1995). Monsoon season total rainfall for 29 different meteorological sub-divisions over India from 1871 to 2000 along with sub-divisional rainfall data at a district level have been processed by Parthasarathy *et al*. (1995) and have been freely available from the website of the Indian Institute of Tropical Meteorology.

Copyright © 2008 Royal Meteorological Society

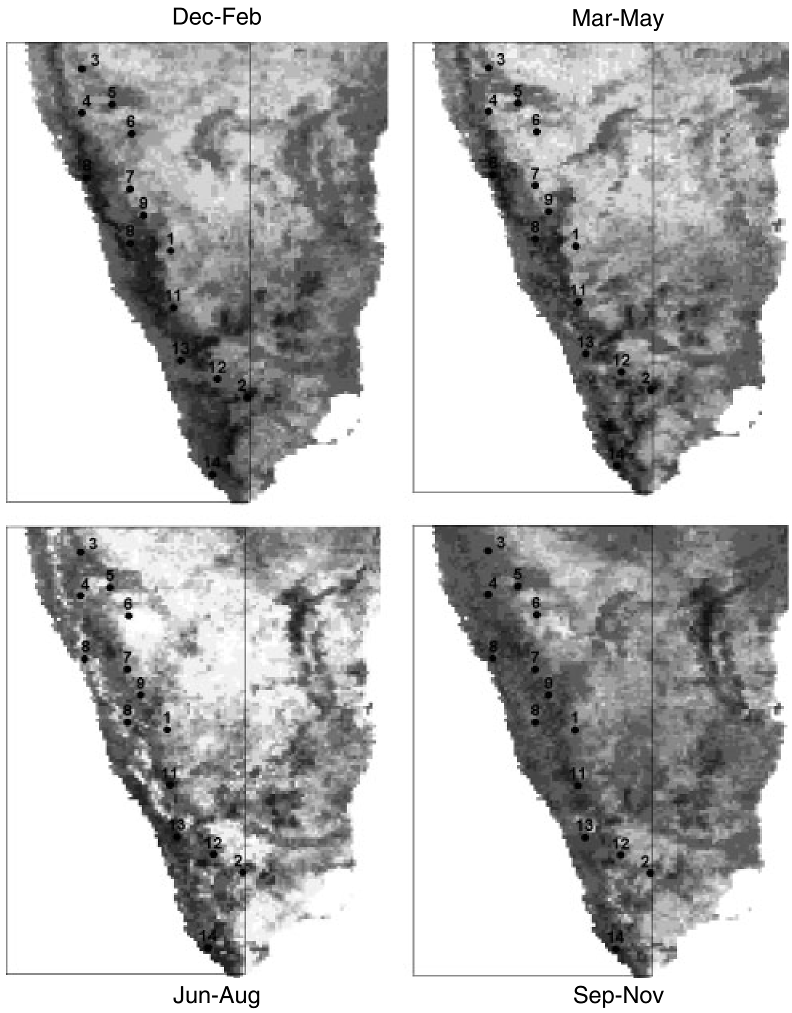

Figure 2. NDVI variations during different seasons.

3.2. Bio-climatic indices, meteorological and topographic data

Using the climate data for each location (Table II), we computed different bio-climatic indices. These included:

(1) Lang *et al*. (1976) rain factor (RF)

It is calculated as the ratio between mean precipitation and mean temperature, or $RF = P \cdot T^{-1}$. In this study, we used mean monthly precipitation (mm) and mean monthly temperature (°C) to arrive at the annual rain factor for different sites.

(2) Martonne's (1926) aridity index (AI)

It is calculated as,

$$AI = PY/(TY + 10)$$

where PY is the annual precipitation (mm), TY is the annual temperature (°C). In order to get rid of eventual negative mean temperature values, a value of 10 is added to the mean temperature.

(3) Rivas-Martínez *et al*. (1999) continentality index (CI)

This index expresses the range between the maximum temperature (T_{max} in °C) and the minimum temperature (T_{min} °C) for the period considered. $CI = T_{max} - T_{min}$. In our case, we computed CI for different years (1990–2003).

(4) Rivas-Martínez *et al*. (1999) thermicity index (TI)

This index sums all the relevant temperature measurements,

$$TI = T + T_{min} + T_{max}$$

or where T is the mean temperature (°C), Tmin is the minimum mean temperature (°C) and T_{max} is maximum mean temperature (°C) for the period considered. In our case, we used monthly values of temperature (°C) to arrive at annual TI for individual years (1990–2003).

(5) Emberger's (1942) pluviothermic ratio (PR)

Emberger's ratio takes into account the thermal amplitude of a database, and is calculated as,

$$PR = 2P \times [(T_{max} + T_{min}) \times (T_{max} - T_{min})]^{-1}$$

where P is the total annual precipitation (mm), T_{max} is the mean maximum temperature for the period considered, and T_{min} is the mean minimum temperature. In our case, to arrive at the annual maximum and minimum temperatures, we used monthly values of temperature (°C) and then combined it with the total annual precipitation

Copyright © 2008 Royal Meteorological Society

DOI: 10.1002/joc

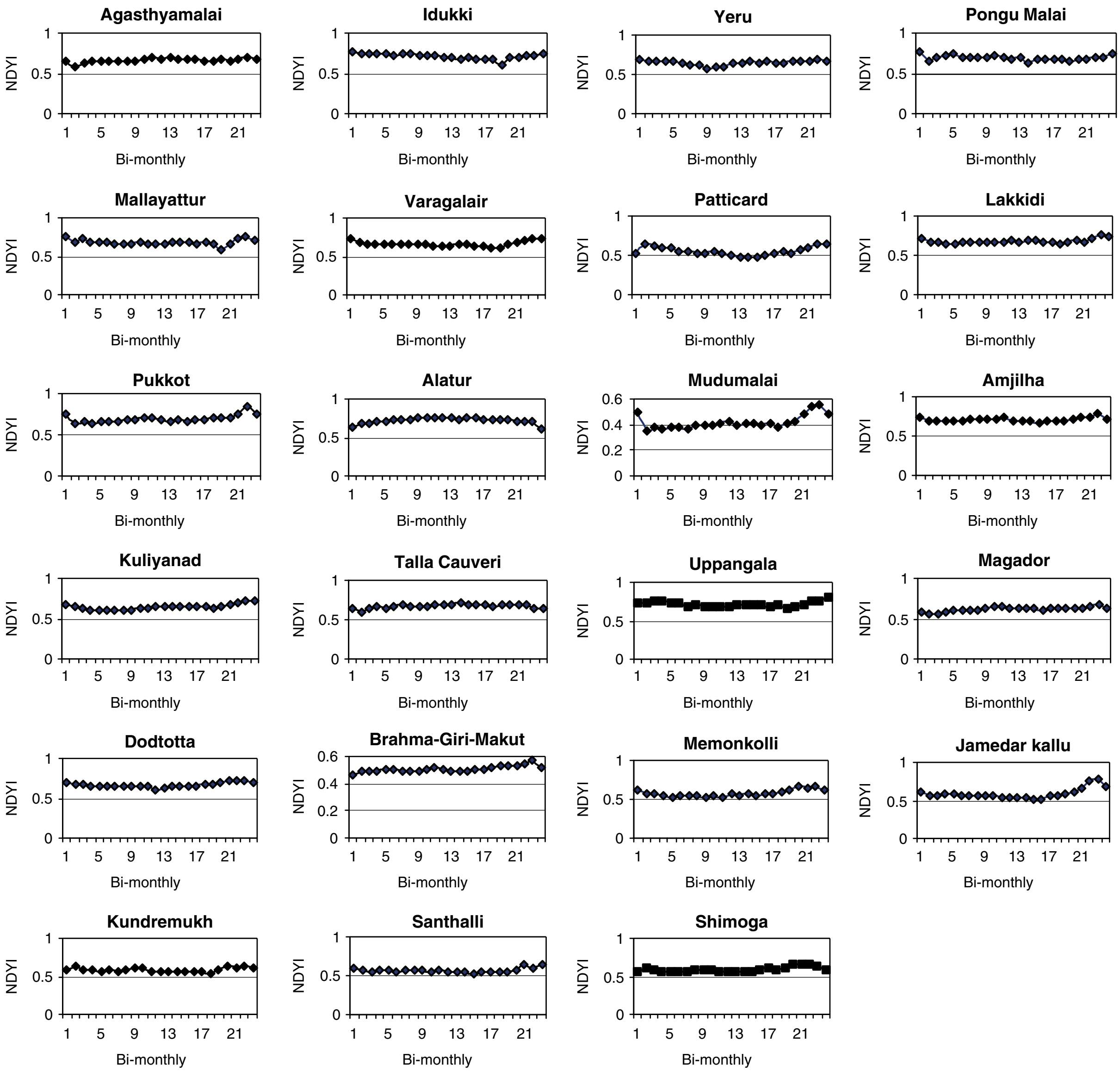

Figure 3. Bi-monthly NDVI data for different sites. Data from 1990 to 2003 has been averaged for variations. This figure is available in colour online at www.interscience.wiley.com/ijoc

(mm) to arrive at the PR using the above equation. The index value has been computed for different years.

In addition to these indices, we used elevation mean (ELE), slope mean (SLP), aspect mean (ASP), average precipitation (AVG-P) and different combinations of averaged precipitation (ppt in mm), i.e. precipitation of the wettest quarter (PWQ) (June–August ppt), precipitation of the driest quarter (PDQ) (March–May ppt) and precipitation during the winter quarter (PCQ) (December–February ppt). For deriving the topographic information (slope, aspect, elevation), we used the GTOPO 30 digital elevation model (DEM) (USGS, 2006) with a horizontal grid spacing of 30 arc s (~1 km). While elevation (m) values are directly read from GTOPO30, slope (%) and aspect (in degrees) were derived using spatial analyst extension in ArcView geographic information systems (GIS). When the Spatial Analyst extension is loaded into ArcView GIS, inbuilt functions for slope and aspect appear on the surface menu. These functions have been used specifically to compute slope and aspect for the entire study region. The algorithm description using spatial analyst extension for deriving slope and aspect are provided in ARCVIEW spatial analyst manual (ESRI, 1996). Variations in bio-climatic indices, precipitation as well as topography in the study area are shown in Figures 4, 5(a), (b) and 6

3.3. PLS regression

We used Partial Least Square (PLS) regression to assess the variations in NDVI along the latitudinal gradients with respect to bio-climatic and meteorological indices. PLS regression is one of the robust multivariate techniques that combine features from principal component analysis and multiple regression (Wold, 1985). It is particularly useful when we need to predict a set of dependent variables from a (very) large set of independent variables (predictors). The dependent variable in our case

Copyright © 2008 Royal Meteorological Society

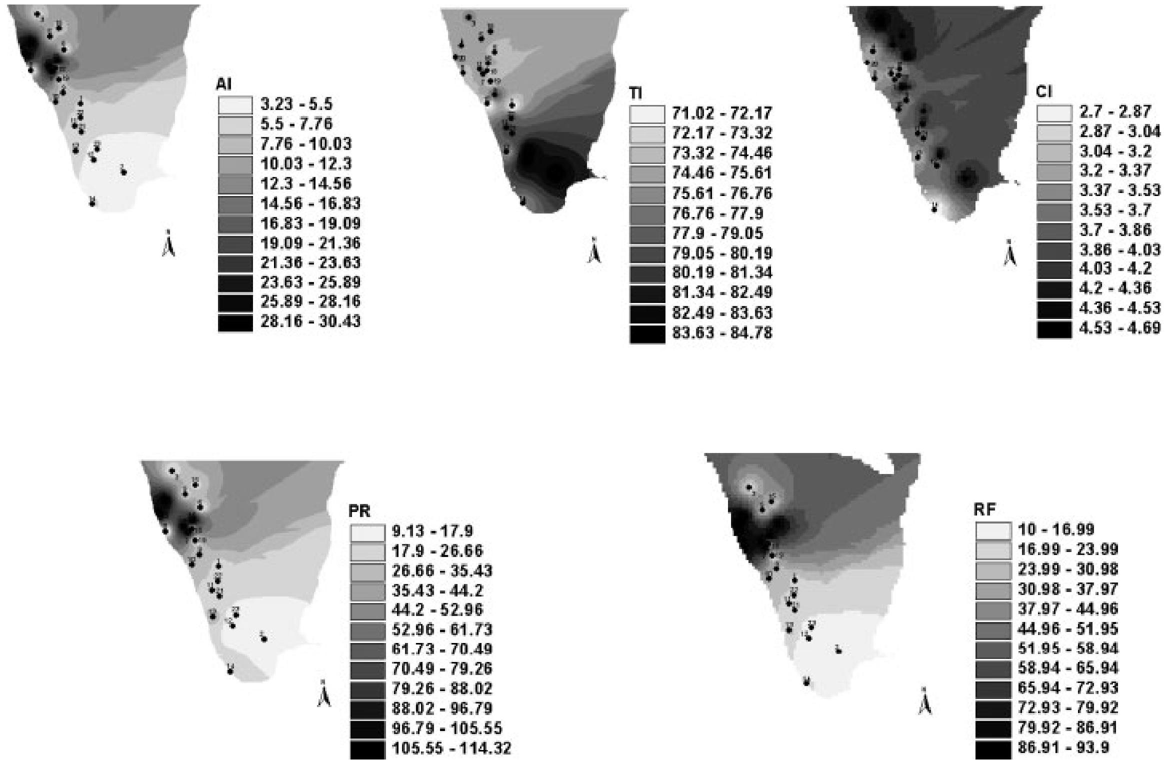

Figure 4. Bio-climatic index maps for the Western Ghats region. The site location details are given in Table II.

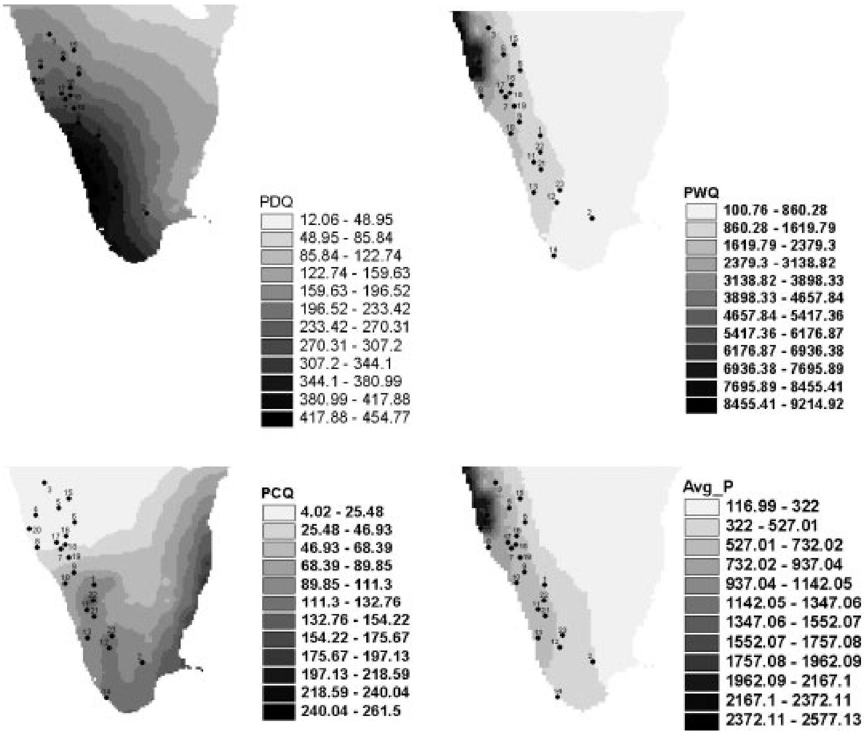

Figure 5. Precipitation variations in the study region. The site location details are given in Table II.

was NDVI at different latitudinal gradients (Table II) and independent predictors included bio-climatic indices, meteorological and topographic variables (Table III). Most importantly PLS is a predictive technique that can handle many independent variables, even when these display multi-colinearity (Wold, 1981). It is based on linear transition from a large number of original descriptors to a small number of orthogonal factors (latent variables) providing the optimal linear model in terms of predictivity (Neter *et al.*, 1996). In other words, factors are mutually independent (orthogonal) linear combinations of original descriptors. Unlike some similar

Copyright © 2008 Royal Meteorological Society

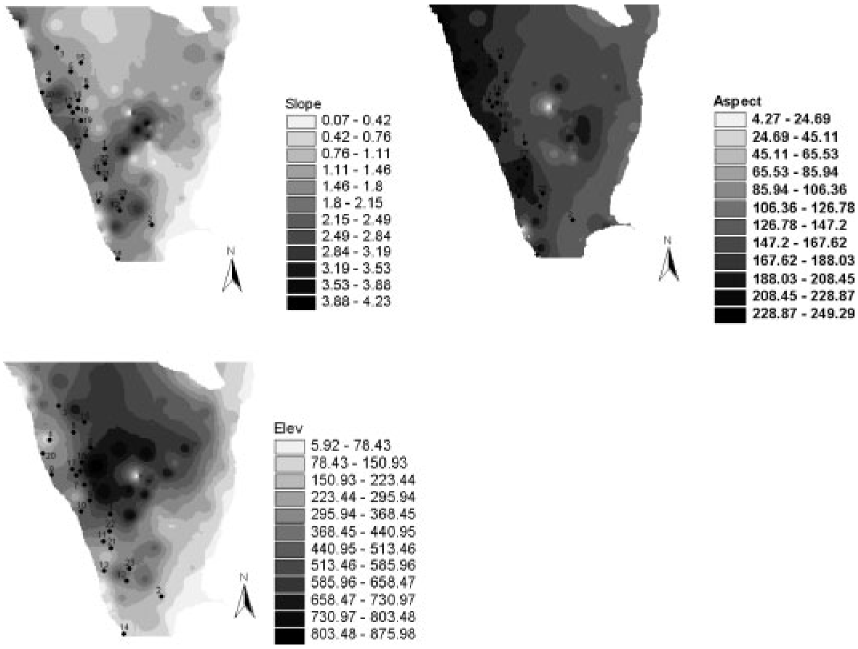

Figure 6. Elevation (m), Slope (%) and Aspect (degrees) derived from GTOPO30 digital elevation model.

approaches, e.g. principal component regression (PCR), latent variables are chosen in such a way as to provide maximum correlation with a dependent variable; thus, PLS model contains the smallest necessary number of factors. With the increasing number of factors, a PLS regression model converges to that of an ordinary multiple linear regression model (Chong and Jun, 2005). The number of significant principal components for the PLS algorithm is determined using the cross-validation method. With cross-validation, some samples are kept out of the calibration and used for prediction. The process is repeated so that all samples are kept out once. The value for the left out compound is then predicted and compared with the known value. The prediction error sum of squares (PRESS) obtained in the cross-validation is calculated each time that a new PC is added to the model. The optimum number of PCs is concluded as the first local minimum in the PRESS *versus* PC plot. PRESS is defined as

$$PRESS = \sum_{i}^{n} (\hat{y} - y)^2$$

where 'y' *(hat)* is the estimated value of the ith object and 'y' the corresponding reference value of this object. The goodness-of-fit is evaluated by root mean squared error (RMSE), which is defined as

$$RMSE = \sqrt{PRESS/n}$$

where n is the number of geographical sites where NDVI value has been extracted. A descriptor's selection was performed in order to limit the amount of potentially irrelevant or redundant information. Further, the averaged NDVI values for individual years from 1990 to 2003 at different sites were used as dependent variables with bio-climatic indices and other meteorological and topographic parameters as predictors (Table III). Furthermore, we used Box-Cox transformation procedure for correcting non-normality in the data.

Table III. Environmental variables used for predicting spatial variation in NDVI across 23 different forested sites.

S. No	Bio-climatic, meteorological and topographic parameters	Range of values
1	Modified Lang *et al.*'s rain factor (RF)	9.98–94.4
2	Martonne's aridity index (AI)	3.23–30.44
3	Rivas-Martínez continentality index (CI)	2.8–4.7
4	Rivas-Martínez thermicity index (TI)	1.53–2.92
5	Average precipitation (AVG-P) (mm)	1084.21
6	Emberger's pluviothermic ratio (PR)	17.44–114.32
7	Aspect (ASP) (degrees)	136.90–231.96
8	Precipitation of the driest quarter (PDQ) (mm)	187–431
9	Precipitation of the coolest quarter (PCQ) (mm)	391–681
10	Slope (SLP) (degrees)	5–58
11	Precipitation of the wettest quarter (PWQ) (mm)	601–5490
12	Elevation (ELE) (m)	600–1800

4. Analysis and results

The range of values obtained for different environmental variables/predictors are given in Table III, suggesting a good amount of heterogeneity in the bio-climatic, meteorological and topographic parameters. The average annual NDVI values for several sites were above 0.5 suggesting the evergreen/semi-evergreen nature of

Copyright © 2008 Royal Meteorological Society

DOI: 10.1002/joc

vegetation. Also, the coefficient of variation in seasonal NDVI, which is a relative measure of dispersion about the mean for individual sites, varied from 0.05–0.10 suggesting very low intra-annual variability, due to the evergreen nature. Results from PLS regression are shown in Tables IV and V. PLS regression analysis suggested the two-component model to be the best, explaining nearly 71% of variance in the NDVI datasets with relatively good R^2 value of 0.78 and predicted R^2 value of 0.74. In order to arrive at the optimal number of components for the above PLS model involving NDVI at different sites and bio-climatic, meteorological and topographic variables as predictors, we used cross-validation steps. One of the important steps in cross-validation process is PRESS statistic. The PRESS statistic gives a good indication of the predictive power of the model, and a lower value of this statistic is desirable. Thus, of the two components identified from PLS regression, the second component had lowest PRESS statistic (Table IV). Further, the predicted R^2 indicates how well the model predicts responses for new observations, whereas R^2 indicates how well the model fits the data. Predicted R^2 can prevent over-fitting the model, and is more useful than adjusted R^2 for comparing models because it is calculated with observations not included in model calculation. Larger values of predicted R^2 suggest models of greater predictive ability. Both the R^2 and predicted R^2 of the two-component model in our case were relatively good suggesting the model to be the best fit. Most importantly, we used the p-value to analyse whether the regression coefficients obtained from PLS are significantly different from zero. The p-value in our case is smaller than a pre-selected alpha level of 0.05 indicating that the model is significant and at least one regression coefficient is not zero. The regression coefficients represents weights or multipliers, provided by the PLS regression equation. The regression coefficient can be interpreted as the amount of change that is expected to occur in the criterion per unit change in that predictor when statistical control has occurred for all other variables in the analysis. The sign of the coefficient indicates direction of the change (Table V). The standardized coefficient plot provides both the sign and magnitude of the coefficients for each predictor (Figure 7).

The plot (Figure 7) also makes it easier to quickly identify predictors that are more or less important in the model. Thus, in our case, the most important positive

Table IV. Model Selection, validation and variance components explained for NDVI. The p-value for the responses is less than 0.005, indicating that the model is significant, and at least one regression coefficient is not zero.

Components	X Variance	R-Sq	PRESS	R-Sq (pred)	p-value
1	0.413223	0.622	434.17	0.593	0.000
2	0.714367	0.784	363.59	0.7407	

Table V. Regression coefficients and standardized coefficients obtained from PLS regression using NDVI as a dependent variable and bio-climatic, meteorological and topographic variables as predictors.

	Coefficients
Constant	88.9024
RF	−0.1486
AI	−0.1477
CI	3.1410
TI	−0.5308
AVG-P	0.1664
PR	−0.1897
ASP	−0.3226
PDQ	10.4886
PCQ	21.0701
SLP	−1.0330
PWQ	7.2331
ELE	1.2541

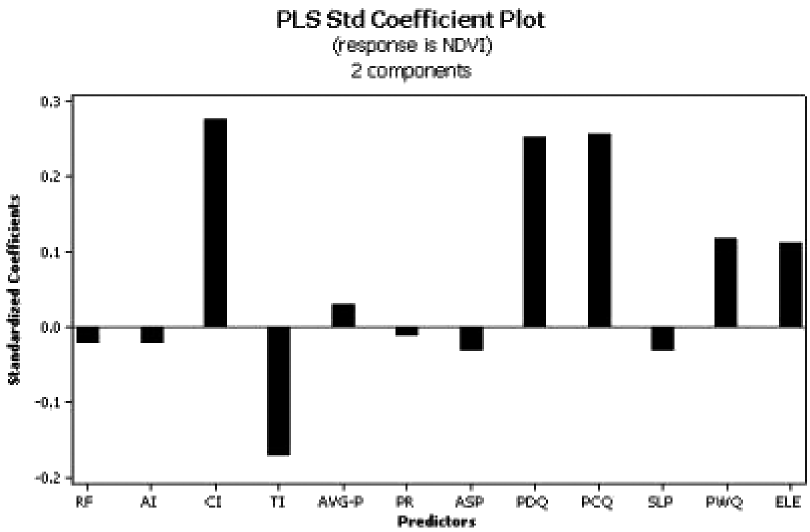

Figure 7. Standardized coefficient plot showing the sign and magnitude for different predictors of NDVI.

Copyright © 2008 Royal Meteorological Society

DOI: 10.1002/joc

predictors included CI, AVG-P, PDQ, PCQ, PWQ, ELE, and negative predictors included RF, AI, TI, PR, ASP and SLP. Further, of the positive predictors, CI, PDQ and PCQ were more distinct, and among negative predictors, TI clearly had higher magnitude than other predictors. The indices of RF, AI and PR that are a combination of precipitation and temperature could not capture the variation in NDVI datasets, most possibly due to high site-level variations in climatic parameters. Relating to temperature, TI which is a sum of mean temperature plus minimum and maximum temperature showed negative sign in comparison to Riva's CI, an indicator of range of temperature, which showed positive sign. Further, slope is an indicator of the rate of change of elevation and steepness of the terrain. While, aspect is more related to direction of slope. The negative sign of slope and aspect against NDVI seems reasonable because of the solar radiance, which affects soil moisture variations. Flat areas at the bottom of valleys are always moist and shadowy, with steep slopes receiving more solar energy but relatively dry. Such conditions are not conducive for vegetation growth and vigor (less NDVI). Finally, the loading plot (Figure 8) represents the scatter plot of the predictors projected onto the first and second components. It shows the x-loadings for the second component plotted against the x-loadings of the first component. Each point, representing a predictor, is connected to (0,0) on the plot. The loading plot shows how important the predictors are to the first two components. While the Table IV explains the variance in the datasets, the loading plot indicates how important the predictors are in the x-space. Predictors with longer lines and having greater loadings in the components are more important in the model. Also, the angles between the lines represent the correlation between the predictors. Smaller angles indicate that predictors are highly correlated. Thus, PDQ, PCQ and CI had higher loadings, while TI and slope had smaller loading values. Further, AI and RF showed relatively higher correlations than others. These results and interpretations from PLS regression with respect to NDVI and other independent predictors clearly suggests that (1) bio-climatic indices that integrate both temperature and precipitation parameters behaved relatively poorer than individual temperature or precipitation indicators (2) Indicators that combined precipitation parameters had much more positive influence than topographic parameters (3) Of all the indicators, CI, which is an indicator of temperature range, had higher influence on NDVI.

5. Discussion and conclusions

Literature review clearly suggests that climatic factors such as precipitation and temperature play an important role in the growth and development of natural vegetation (Mather and Yoshioka, 1968; Wang *et al.*, 2003; Suzuki *et al.*, 2006). Our results from PLS regression in the Western Ghats region captured the important climatic parameters governing vegetation vigour. Evergreen forests are found in regions where rainfall exceeds 2000 mm.Evergreen species retain a full canopy all the year round and the decline in canopy fullness in the dry season is less than 10% (depicted as low coefficient of variation in NDVI). In contrast, deciduous species lose all leaves for at least one, but usually two to four months of each year (can result in high coefficient of variation in NDVI). Most importantly, results clearly suggested that NDVI variations in the Western Ghats region are mostly controlled by the seasonality of rainfall. In the Western Ghats region, rainfall seasonality is mainly attributed to

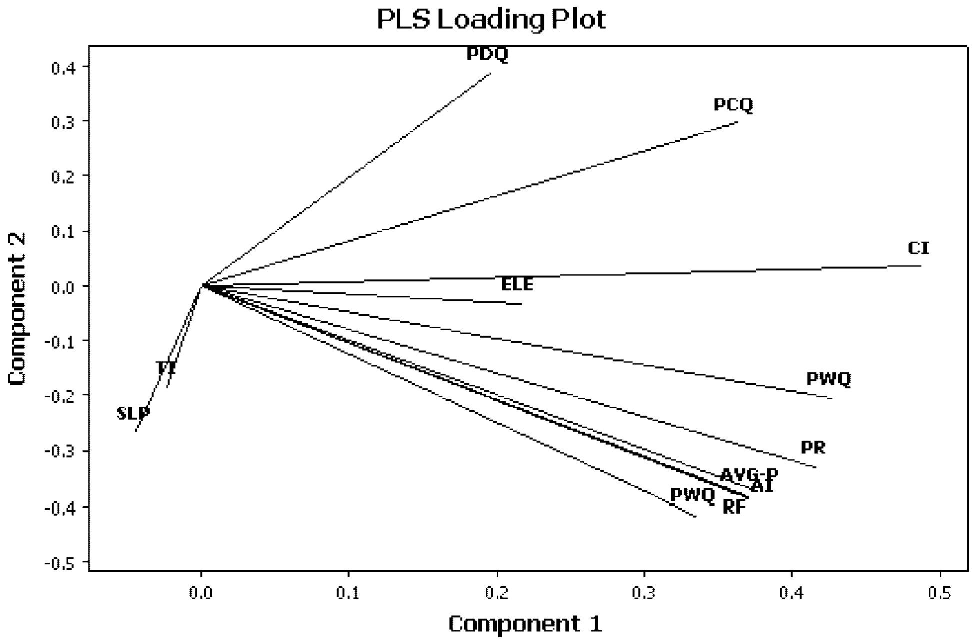

Figure 8. PLS loading plot showing the predictors projected onto the first and second components. The predictors were standardized to infer the magnitude.

Copyright © 2008 Royal Meteorological Society

the Asian summer monsoon, which brings heavy rains from May to September. The arrival–withdrawal of the southwest monsoon and the limited inland penetration of the rains create strong south-to-north and west-to-east gradients in rainfall intensities and seasonality (thus affecting dry season length) all over western South India. Moreover, this natural barrier creates a strong west-to-east gradient of decreasing rainfall (Gadgil and Joshi, 1983; Singh, 1986, Pascal, 1992; Gunnell, 1997). These rainfall variations clearly influence the vegetation vigor (NDVI). With respect to NDVI response to rainfall, several studies reported that vegetation does not respond to immediate rainfall, rather it is affected by the history of soil moisture buildup (cumulative rainfall) (Davenport and Nicholson, 1993; Wang *et al.*, 2003). For example, Richard and Poccard (1998) studied the sensitivity of NDVI to seasonal and inter-annual rainfall variations in southern Africa and reported the strongest correlations when NDVI monthly values are compared with the preceding bi-monthly rainfall amounts, attesting to a time response of one to two months. Further, their analysis using multivariate statistics, suggested differences in rainfall-NDVI associations based on geographical conditions, Farrar *et al*. (1994) found that while the correlation between NDVI and precipitation is highest for a multi-month average, NDVI is controlled by soil moisture in the concurrent month. In our case too, the strongest predictors included all the seasonal precipitation parameters, i.e. precipitation during the driest quarter, wettest quarter as well as coolest quarter. Although the magnitude of precipitation events during the driest quarter and coolest quarter were relatively higher (Figure 7) than the wettest quarter, they all exhibited positive signs in the regression coefficients. Further, the relatively lower magnitude in PWQ may be attributed to the saturation effect of NDVI to seasonal rainfall. For example, several studies reported the relationship between NDVI to rainfall to be no longer sensitive to rainfall variations beyond a given rainfall threshold, particularly in wet tropical areas (Davenport and Nicholson, 1993; Wang *et al*., 2003). This rainfall amount has been shown to be 200 mm month^{-1} over equatorial Africa (Richard and Poccard, 1998), East Africa at 1200 mm/yr^{-1} (Nicholson and Farrar, 1994) or 600 mm/yr^{-1} (Fuller and Prince, 1996) above which NDVI curve saturates. In the case of the Western Ghats, the rainfall range during the wettest quarter is from 601 to 5490 mm/yr^{-1}, which is far higher than the values reported above, suggesting the saturation of NDVI. Also, earlier studies in the Western Ghats region reported that the difference between the evergreen forest types (mainly species composition) are related to the lowering of the temperature with altitude and the increase in the dry period with latitude (Pascal, 1992). The Rivas CI, which is an indicator of the range of temperature, clearly seems to highlight this aspect. Likewise, NDVI was positively correlated with elevation as observed from regression coefficients. As the phenological attributes, such as vegetation vigor from NDVI reflect the response to the earth's climate and hydrological regimes, use of accurate bio-meteorological indicators that govern these changes can help in developing classification schemes using remotely sensed data. For example, Norwine and Greegor (1983) used AVHRR data for vegetation classification and concluded that statistical models combining spectral and climatic indices account for distribution of major vegetation types and that such models have promise as a technique for vegetation stratification and monitoring. From this study, we infer that in the case of evergreen forests of the Western Ghats, seasonal precipitation indicators along with temperature range can be used successfully to delineate these forest types from others. Also, our results can be effectively used to parameterize and modify the models relating to phenology, including monitoring biospheric activity, developing prognostic phenology models, and for deriving land cover maps in the study region. We also infer the need to initiate phenology network stations across India covering highly diverse forests that will include simple and effective means to input, report, and utilize phenological ground-based observations for a variety of ecological, climatic and agricultural applications. Such a network can also capitalize on a wide variety of remote-sensing products and meteorological data already available from different governmental departments in the Indian region.

Acknowledgements

The authors gratefully acknowledge the Director, Agroecosystem Management Program, The Ohio State University, for encouragement and facilities. Comments and suggestions received from scientists of the National Remote Sensing Agency, Department of Space, Government of India, and the Indian Institute of Remote Sensing, Dehradun, India, on the draft manuscript, are gratefully acknowledged. The authors are extremely thankful to the anonymous reviewers for providing useful comments on the first version of the manuscript.

References

Ashton PS, Givnish TJ, Appanah S. 1988. Staggered flowering in the Diperocarpaceae: new insights into floral induction and the evolution of mast fruiting in the seasonal tropics. *American Naturalist* **231**: 44–66.

Borchert R. 1998. Responses of tropical trees to rainfall seasonality and its long-term changes. *Climatic Change* **39**: 2–3.

Champion HG, Seth SK. 1968. *A Revised Survey of the Forest Types of India*. Government of India Press: New Delhi.

Chen X, Xu C, Tan Z. 2001. The analysis of relationships among plant community phenology and seasonal metrics of Normalized Difference Vegetation Index on the northern part of the monsoon region of China. *International Journal of Biometeorology* **45**: 170–177.

Chong IG, Jun CH. 2005. Performance of some variable selection methods when multicollinearity is present. *Chemometrics And Intelligent Laboratory Systems* **78**: 103–112.

Davenport ML, Nicholson SE. 1993. On the relation between rainfall and the Normalized Difference Vegetation Index for diverse vegetation types in East Africa. *International Journal of Remote Sensing* **14**(12): 2369–2389.

David H, Phillip F. 2004. Phenological description of natural vegetation in southern Africa using remotely sensed vegetation data. *Applied Vegetation Science* **7**: 19–28.

Copyright © 2008 Royal Meteorological Society

Emberger L. 1942. Un projet d'une classification des climats du point de vue phytogéographique. *Bulletin de la Société d'Histoire Naturelle de Toulouse* **77**: 97–124.

ESRI. 1996. *Using the ArcView Spatial Analyst*. Environmental Systems Research Institute, Inc: Redlands: CA. 350pp.

Farrar TJ, Nicholson SE, Lare AR. 1994. The influence of soil type on the relationships between NDVI, rainfall and soil moisture in semiarid Botswana. II. NDVI response to soil moisture. *Remote Sensing of Environment* **50**: 121–133.

Fuller DO, Prince SD. 1996. Rainfall and foliar dynamics in tropical Southern Africa: potential impacts of global climatic change on savanna vegetation. *Climatic Change* **33**: 69–96.

Gadgil S, Joshi NV. 1983. Climatic clusters of the Indian region. *Journal of Climatology* **3**: 47–53.

Gensuo JJ, Howard EHE, Walker DA. 2002. Spatial characteristics of AVHRR-NDVI along latitudinal transects in northern Alaska. *Journal of Vegetation Science* **13**: 315–326.

Goetz SJ, Fiske GJ, Bunn AG. 2006. Using satellite time-series data sets to analyze fire disturbance and forest recovery across Canada. *Remote Sensing of Environment* **101**: 352–365.

Goward SA. 1989. Satellite bioclimatology. *Journal of Climate* **7**: 710–720.

Goward SN, Tucker CJ, Dye DG. 1985. North American vegetation patterns observed with the NOAA-7 advanced very high-resolution radiometer. *Vegetatio* **64**: 3–14.

Gunnell Y. 1997. Relief and climate in South-Asia: the influence of the Western Ghats on the current climate pattern of Peninsular India. *International Journal of Climatology* **17**: 1169–1182.

Holben BN. 1986. Characterization of maximum value composites from temporal AVHRR data. *International Journal of Remote Sensing* **7**: 1417–1434.

Huete AR. 1988. A soil adjusted vegetation index (SAVI). *Remote Sensing of Environment* **25**: 295–309.

Ichii K, Kawabata A, Yamaguchi Y. 2002. Global correlation analysis for NDVI and climatic variables and NDVI trends: 1982–1990. *International Journal of Remote Sensing* **23**(18): 3873–3878.

Jensen JR. 2000. *Remote Sensing of the Environment: An Earth Resource Perspective*, 2nd edn. Prentice-Hall, Inc.: Upper Saddle River, NJ; 544.

Jolly WM, Running SW. 2004. Effects of precipitation and soil water potential on drought deciduous phenology in the Kalahari. *Global Change Biology* **10**: 303–308.

Juarez R, Liu WT. 2001. FFT analysis on NDVI annual cycle and climatic regionality in northeast Brazil. *International Journal of Climatology* **21**: 1803–1820.

Justice CO, Holben BN, Gwynne MO. 1986. Monitoring East African vegetation using AVHRR data. *International Journal of Remote Sensing* **7**: 1453–1474.

Karlsen SR, Elvebakk A, Høgda KA, Johansen B. 2006. Satellite-based mapping of the growing season and bioclimatic zones in Fennoscandia. *Global Ecology and Biogeography* **15**: 416–430.

Kemp PR, Gardetto PE. 1982. Photosynthetic pathway types of evergreen rosette plants (Liliaceae) of the Chihuahuan desert. *Oecologia* **55**: 149–156.

Kogan FN. 1997. Global Drought Watch from Space. *Bull. Amer. Meteor. Soc*. **78**(4): 621–636.

Lang OL, Kappen L, Schulze ED. 1976. *Water and Plant Life*. Springer: Berlin, Heidelberg, New York.

Los SO. 1998. Estimation of the Ratio of Sensor Degradation Between NOAA AVHRR Channels 1 and 2 from Monthly NDVI Composites. *IEEE Transactions on Geoscience and Remote Sensing* **36**(1): 206–213.

Malingreau J-P. 1986. Global vegetation dynamics: satellite observations over Asia. *International Journal of Remote Sensing* **7**: 1121–1146.

Malo AR, Nicholson SE. 1990. A study of rainfall and vegetation dynamics in the African Sahel using normalized difference vegetation index. *Journal of Arid Environments* **19**: 1–24.

Martonne E. 1926. *Une Nouvelle Fonction Climatique: L'indice D'aridité*. La Météo, Association des Météorologues du Québec: Québec; 449–458.

Mather JR, Yoshioka G. 1968. The role of climate in the distribution of vegetation. *Annals of the Association of American Geographers* **58**: 29–41.

Moulin S, Kergoat L, Viovy N. 1997. Global-scale assessment of vegetation phenology using NOAA/AVHRR satellite measurements. *Journal of Climate* **10**: 1154–1170.

Myers N, Mittermeier RA, Mittermeier CG, da Fonesca GAB, Kent J. 2000. Biodiversity hotspots for conservation priorities. *Nature* **403**: 853–858.

Myneni RB, Keeling CD, Tucker CJ, Asrar G, Nemani RR. 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. *Nature* **386**: 698–702.

Nemani R, Keeling CD, Hashimoto H, Jolly WM, Piper SC, Tucker CJ, Myneni R, Running W. 2003. Climate driven increases in Global Terrestrial Net Primary Production from 1982–1999. *Science* 1562–1563.

Neter J, Kutner MH, Nachtsheim CJ, Wasserman W. 1996. *Applied Linear Regression Models*, 3rd edn. Irwin Book Team: Chicago, IL.

Nicholson SE, Farrar TJ. 1994. The influence of soil type on the relationships between NDVI, rainfall and soil moisture in semiarid Botswana. I.NDVI response to rainfall. *Remote Sensing of Environment* **50**: 107–120.

Nightingale JM, Phinn SR. 2003. Assessment of relationships between precipitation and satellite derived by vegetation condition within south Australia. *Australian Geographical Studies* **41**(2): 180–195.

Norwine J, Greegor DH. 1983. Vegetation classification based on AVHRR satellite imagery. *Remote Sensing of Environment* **13**: 69–78.

Opler PA, Frankie GW, Baker HG. 1976. Rainfall as a factor in the release, timing and synchronization of anthesis by tropical trees and shrubs. *Journal of Biogeography* **3**: 231–236.

Parthasarathy B, Munot AA, Kothawale DR. 1995. Monthly and seasonal rainfall series for All-India homogeneous regions and meteorological subdivisions: 1871–1994. Research Report RR-065. Contributions from Indian Institute of Tropical Meteorology: Pune 411 008.

Paruelo JM, Lauenroth WK. 1998. Inter annual variability of NDVI and its relationship to climate for North American shrub lands and grasslands. *Journal of Biogeography* **25**: 721–733.

Pascal JP. 1992. Evergreen forests of the Western Ghats – Structural and Functional trends. In *Tropical Ecosystems: Ecology and Management*, Singh KP, Singh JS (eds). Wiley Eastern Limited: New Delhi; 385–408.

Pascal J-P, Shyam Sunder V, Meher-Homji VM. 1982a. Forest map of South India – Sheet: Mercara-Mysore. Karnataka and Kerala Forest Departments and Institut français, Pondichéry, India.

Pascal J-P, Shyam Sunder V, Meher-Homji VM. 1982b. Forest map of South India – Sheet: Shimoga. Karnataka and Kerala Forests Departments and Institut français, Pondichéry, India.

Potter CS, Brooks V. 1998. Global analysis of empirical relationships between annual climate and seasonality of NDVI. *International Journal of Remote Sensing* **19**: 2921–2948.

Ramesh BR, Pascal JP. 1991. Distribution of endemic arborescent evergreen species in the Western Ghats. *Proceedings of the Symposium On Rare, Endangered and Endemic Species of the Western Ghats*. Kerala Forest Department: Tiruvananthapuram; 1–7.

Reed BC, White M, Brown JF. 2003. Remote sensing phenology. In *Phenology: An Integrative Environmental Science*, chap.5.1, Schwartz MD (ed.). Springer: New York; 365–381.

Reich PB, Borchert R. 1984. Water stress and tree phenology in a tropical dry forest in the tropical dry forest lowlands of Costa Rica. *Journal of Ecology* **72**: 61–74.

Richard Y, Poccard I. 1998. A statistical study of NDVI sensitivity to seasonal and interannual rainfall variations in Southern Africa. *International Journal of Remote Sensing* **19**(15): 2907–2920.

Rivas-Martínez S, Sánchez-Mata D, Costa M. 1999. North American boreal and Western temperate forest vegetation (Syntaxonomical synopsis of the potential natural plant communities of North America II). *Itinera Geobotánica* **12**: 5–31.

Sakai S. 2001. Phenology diversity in tropical forests. *Population Ecology* **43**: 77–86.

Schultz P, Halpert M. 1995. Global analysis of the relationships among a vegetation index, precipitation and land surface temperature. *International Journal of Remote Sensing* **16**: 2755–2777.

Schwartz MD, Reed BC. 1999. Surface phenology and satellite sensor-derived onset of greenness: An initial comparison. *International Journal of Remote Sensing* **20**: 3451–3457.

Singh N. 1986. On the duration of the rainy season over different parts of India. *Theoretical and Applied Climatology* **37**: 51–62.

Slayback DA, Pinzon JE, Los SO, Tucker CJ. 2003. Northern Hemisphere photosynthetic trends 1982–99. *Global Change Biology* **9**: 1–15.

Suzuki R, Masuda K. 2004. Interannual covariability found in evapotranspiration and satellite-derived vegetation indices over

Copyright © 2008 Royal Meteorological Society

DOI: 10.1002/joc

northern Asia. *Journal of the Meteorological Society of Japan* **82**(4): 1,233–1,241.

Suzuki R, Tanaka S, Yasunari T. 2000. Relationships between meridonal profiles of satellite-derived vegetation index (NDVI) and climate over Siberia. *International Journal of Climatology* **20**: 955–967.

Suzuki R, Xu J, Motoya K. 2006. Global analyses of satellite-derived vegetation index related to climatological wetness and warmth. *International Journal of Climatology* **26**: 425–438.

Tateishi R, Kajiwara K. 1992. Global land cover monitoring by AVHRR NDVI data. *Earth Environment* **7**: 4–14.

Tateishi R, Ebata M. 2004. Analysis of phenological change patterns using 1982–2000. Advanced Very High Resolution Radiometer (AVHRR) data. *International Journal of Remote Sensing* **25**(4): 2287–2300.

Townshend JRG, Justice CO. 1986. Analysis of the dynamics of African vegetation using the normalized difference vegetation Index. *International Journal of Remote Sensing* **7**: 1435–1445.

Tucker CJ, Sellers PJ. 1986. Satellite remote sensing of primary production. *International Journal of Remote Sensing* **7**: 1395–1416.

Tucker CJ, Pinzon JE, Brown ME. 2004. Global Inventory Modeling and Mapping Studies, NA94apr15b.n11-VIg, 2.0, Global Land Cover Facility, University of Maryland, College Park, 04/15/1994.

Tucker CJ, Pinzon JE, Brown ME, Slayback D, Pak EW, Mahoney R, Vermote E, El Saleous N. 2005. An Extended AVHRR 8-km NDVI Data Set Compatible with MODIS and SPOT Vegetation NDVI Data. *International Journal of Remote Sensing* **26**(20): 4485–5598.

USGS. 2006. United States Geological Survey, GTOPO 30 data. <http://edc.usgs.gov/products/elevation/gtopo30/gtopo30.html>.

van Schaik CP, Terborgh JW, Wright SJ. 1993. The phenology of tropical forests-Adaptive significance and consequences for primary consumers. *Annual Review of Ecology and Systematics* **24**: 353–377.

Wang JM, Rich PM, Price KP. 2003. Temporal response of NDVI to precipitation and temperature in the central Great Plains, USA. *International Journal of Remote Sensing* **24**(11): 2345–2364.

White MA, Thorton PE, Running SW. 1997. A continental phenology model for monitoring vegetation responses to inter annual climatic variability. *Global Biogeochemical Cycles* **11**(2): 217–234.

Wright SJ, van Schaik CP. 1994. Light and the phenology of tropical trees. *American Naturalist* **143**: 192–1999.

Wold H. 1981. *The Fix-Point Approach to Interdependent Systems*. North Holland: Amsterdam.

Wold H. 1985. Partial least squares. In *Encyclopedia of Statistical Sciences*, Vol. 6, Samuel Kotz, Norman L Johnson (eds). Wiley: New York; 581–591.

Woodward FI, McKee IF. 1991. Vegetation and climate. *Environment International* **17**: 535–546.

Zhou L, Kaufmann RK, Tian Y, Myneni RB, Tucker CJ. 2003. Relation between internannual variations in satellite measures of northern forest greenness and climate between 1982 and 1999. *Journal of Geophysical Research* **108**(D1): 4004, DOI:10.1029/2002JD002510.

Zhou LM, Tucker CJ, Kaufmann RK, Slayback D, Shabanov NV, Myneni RB. 2001. Variations in northern vegetation activity inferred from satellite data of vegetation index during 1981 to 1999. *Journal of Geophysical Research-Atmospheres* **106**(D17): 20069–20083.

Copyright © 2008 Royal Meteorological Society