

## SATELLITE DRIVEN ESTIMATION OF PRIMARY PRODUCTIVITY OF AGRO-ECOSYSTEMS IN INDIA

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Commission VIII, WG VIII/6

**KEY WORDS:** Earth observation, ecosystem modeling, gross primary productivity, SPOT-VEGETATION, agro-ecosystem

### ABSTRACT:

Earth observation driven ecosystem modeling have played a major role in estimation of carbon budget components such as gross primary productivity (GPP) and net primary production (NPP) over terrestrial ecosystems, including agriculture. The present study therefore evaluate satellite-driven vegetation photosynthesis (VPM) model for GPP estimation over agro-ecosystems in India by using time series of the Normalized Difference Vegetation Index (NDVI) from SPOT-VEGETATION, cloud cover observation from MODIS, coarse-grid C<sub>3</sub>/C<sub>4</sub> crop fraction and decadal grided databases of maximum and minimum temperatures. Parameterization of VPM parameters e.g. maximum light use efficiency ( $\epsilon^*$ ) and  $T_{\text{scalar}}$  was done based on eddy-covariance measurements and literature survey. Incorporation of C<sub>3</sub>/C<sub>4</sub> crop fraction is a modification to commonly used constant maximum LUE. Modeling results from VPM captured very well the geographical pattern of GPP and NPP over cropland in India. Well managed agro-ecosystems in Trans-Gangetic and upper Indo-Gangetic plains had the highest magnitude of GPP with peak GPP during kharif occurs in sugarcane-wheat system (western UP) and it occurs in rice-wheat system (Punjab) during Rabi season. Overall, croplands in these plains had more annual GPP ( $> 1000 \text{ g C m}^{-2}$ ) and NPP ( $> 600 \text{ g C m}^{-2}$ ) due to input-intensive cultivation. Desertic tracts of western Rajasthan showed the least GPP and NPP values. Country-level contribution of croplands to national GPP and NPP amounts to  $1.34 \text{ Pg C year}^{-1}$  and  $0.859 \text{ Pg C year}^{-1}$ , respectively. Modeled estimates of cropland NPP agrees well with ground-based estimates for north-western India ( $R^2 = 0.63$  and  $\text{RMSE} = 108 \text{ g C m}^{-2}$ ). Future research will focus on evaluating the VPM model with medium resolution sensors such as AWiFS and MODIS for rice-wheat system and validating with eddy-covariance measurements.

### 1. INTRODUCTION

Global land ecosystems in recent time appeared as major sink of global carbon cycle and curtailing the increasing CO<sub>2</sub> concentration in the atmosphere (Zhao and Running, 2009). Henceforth, the quantification of regional contribution from terrestrial ecosystems to global carbon budget is a necessity. Terrestrial primary productivity is key component of carbon cycle and is quantified as amount of carbon fixed by plants via photosynthesis and accumulated as biomass. As of now most studies related to primary productivity and carbon budget in India and abroad have focused on forest ecosystem due to their potential to sequester high magnitude of atmospheric CO<sub>2</sub>. Agro-ecosystems have received less attention by carbon science groups worldwide and in India, in spite of they covers around 15 million km<sup>2</sup> all over the world and about more than half of land area in India. Besides there are evidences that intensively managed agro-ecosystems act as a CO<sub>2</sub> sink in the terrestrial biosphere (e.g., Law *et al.*, 2002; Barford *et al.*, 2003; Hollinger *et al.*, 2004). Recent model simulation by Bondeau *et al.* (2007) suggested that a net sink of  $0.61\text{--}0.75 \text{ Gt C year}^{-1}$  in the 1990s occurred in global agriculture-related areas. In past, few studies based on crop yield and area statistics yielded a varying estimates of total cropland NPP in India (i.e.,  $0.407 \text{ Pg C}$  in 1989 (Dadhwal *et al.*, 1996; Dadhwal and Chabra, 2002),  $0.63 \text{ Pg C}$  in 1980 (Hingane, 1991). NPP databases from crop statistics are area-based and thus lacking spatial detail required for agro-ecosystem management and ecosystem related services.

Satellite remote sensing has provided unique capability to monitor global and regional dynamics of vegetation properties and has been widely used in net primary productivity assessment (Prince and Goward, 1995; Potter *et al.*, 2003; Running *et al.*, 2004). The remote sensing of NPP mainly follows light use efficiency (LUE) concept (Monteith, 1977) that describes carbon assimilation in plants is proportional to product of light absorption and light use efficiency as nearly constant or approximated for diverse ecosystems :

$$\text{NPP} = \sum \text{PAR} \times \text{FPAR} \times \epsilon \quad (1)$$

Where NPP is net primary productivity for season or year ( $\text{g C m}^{-2}$ ), PAR is photosynthetically active radiation in Mega Joule (MJ), fPAR is fractional of absorbed PAR (unitless) which is quantified from remotely sensed vegetation indices, and  $\epsilon$  is light use efficiency ( $\text{g C MJ}^{-1}$ ) factor. Recently few LUE models (e.g. MODIS algorithm, vegetation photosynthesis model) uses equation (1) to estimate gross primary productivity (GPP) and subsequently NPP with inclusion of mechanistic parameterization of autotrophic respiration (Running *et al.* 2004; Xiao *et al.*, 2004). Recently advent of satellite optical sensors such as SPOT-Vegetation and MODIS covers wide range of wavelength and make it easier to drive GPP or NPP models entirely from satellite observations. In past, NPP assessment over India using LUE models such as GLO-PEM (Prince & Goward 1995) and Carnegie-Ames-Stanford-Approach (CASA) (Potter *et al.* 1993; Field *et al.* 1995) adopted the down-regulators (water/temperature

stress) of maximum light use efficiency ( $\epsilon^*$ ) obtained from meteorological variables which is mostly coarse over space and time (Nayak *et al.*, 2009; Singh *et al.*, 2011). Furthermore, climatological information may not correctly captures stress occurred in managed agroecosystems with variable input of advanced cultivars, fertilizer and irrigation. Recently newer LUE models (e.g. VPM, EC-LUE) have been implemented with the use of stress indices derived from SWIR band as measure of water stress scalar in biospheric NPP models and found that the inclusion of a water stress parameter directly from satellite improves accuracy of NPP modeling (Xiao *et al.* 2005).

Moreover, validation of simulated NPP from satellite driven ecosystem models over agricultural areas is a challenging task where coordinated net-work of eddy-covariance towers are lacking. Validation of model NPP estimates with some independent measure of carbon uptake based on crop statistics holds key importance in carbon cycle research (Lobell *et al.* 2002). In view of improving method for estimating GPP or NPP over vast croplands in India, we chose to apply a relatively new vegetation photosynthesis model with aim of driving model with more satellite remote sensing inputs and subsequently validation with crop NPP assessment from agricultural census data.

## 2. MATERIALS AND METHODS

### 2.1 Overview of VPM model

The VPM model is based on contribution of photosynthetically active vegetation (PAV) and non-photosynthetic vegetation (NPV) to fraction of PAR absorbed by canopy (fPAR). Thus VPM algorithm is based on LUE, PAR, and the fraction of PAR absorbed by photosynthetic active vegetation or chlorophyll (fPAR<sub>chl</sub>):

$$GPP = \epsilon \times fPAR_{chl} \times PAR \quad (2)$$

$$fPAR_{chl} = \alpha \times EVI \quad (3)$$

$$\epsilon = \epsilon^* \times T_{scalar} \times W_{scalar} \times P_{scalar} \quad (4)$$

where  $\epsilon^*$  is maximal light use efficiency.  $T_{scalar}$ ,  $W_{scalar}$  and  $P_{scalar}$  are the down-regulation scalars for the effects of temperature, water and leaf phenology on the LUE of vegetation type, respectively. EVI is the enhanced vegetation index derived from reflectance in blue, Red and NIR wavelength regions.

In general EVI is used in VPM model because GPP is more sensitive to EVI in high biomass areas. In our study we explored use of normalized difference vegetation index (NDVI) based equation for fPAR estimation within VPM because NDVI had a wider range and is more sensitive to low biomass areas of most croplands in arid and semi-arid arid environment. We used fPAR-NDVI relationship developed by Myneni and Williams (1994) based on radiation transfer models that was also found to remain remains robust in the presence of pixel heterogeneity, vegetation clumping, and variations in leaf orientation and optical properties.

$$fPAR = a \times NDVI + b \quad (5)$$

where a and b are empirical constants. In our study, a and b are set to 1.24 and 0.168 according to Sims *et al.* (2005)

$T_{scalar}$  is estimated at each time step, using the equation developed for the Terrestrial Ecosystem Model (Raich *et al.*, 1991):

$$T_{scalar} = \frac{(T - T_{min})(T - T_{max})}{[(T - T_{min})(T - T_{max})] - (T - T_{opt})^2} \quad (6)$$

where, T is daytime mean temperature, obtained as average of maximum and mean temperatures on daily basis.  $T_{min}$ ,  $T_{max}$ , and  $T_{opt}$  are the minimum, maximum and optimum temperature for photosynthetic activities, respectively.

In VPM, water stress effects on photosynthesis in terms of  $W_{scalar}$  was quantified using land surface wetness index (LSWI) that is sensitive to canopy water stress. The LSWI is a linear combination of NIR and SWIR bands and calculated as:

$$LSWI = \frac{\delta_{NIR} - \delta_{SWIR}}{\delta_{NIR} + \delta_{SWIR}} \quad (7)$$

where  $\delta_{NIR}$  and  $\delta_{SWIR}$  are reflectances in NIR (780-890 nm) and SWIR (1580-1750 nm) regions, respectively, for each 10-day composite of SPOT-VEGETATION data in present study. We used LSWI to estimate seasonal dynamics of the water stress scalar ( $W_{scalar}$ ) based on the simple approach of Xiao *et al.* (2005):

$$W_{scalar} = \frac{1 + LSWI}{1 - LSWI_{max}} \quad (8)$$

where  $LSWI_{max}$  is the maximum LSWI within the wheat growing season for individual pixels.

$P_{scalar}$  was set to 1 because of leaf emergence in dominantly growing crops such as rice and wheat is throughout growing season (Xiao *et al.*, 2005)

Net Primary Productivity (NPP) is the balance between GPP and autotrophic respiration ( $R_a$ ) and hence described as:

$$NPP = GPP - R_a \quad (9)$$

The autotrophic respiration is affected by air temperature (T, °C) and gross primary production as describe by the following empirical relationship (Furumi *et al.*, 2002):

$$R_a = GPP * [(1.825 + 1.145T)/100] \quad (10)$$

### 2.2 Parameterization of VPM model

In general, VPM model needs three parameters. Firstly, maximum light use efficiency,  $\epsilon^*$  has to be set which is vegetation dependent. The  $\epsilon^*$  can be parameterized as ecosystem quantum yield based on the Michaelis-Menten light response function. In the present study, maximum ecosystem yield parameterized based on eddy-covariance measurements over wheat was taken as representative of  $C_3$  crops (1.37 g C MJ<sup>-1</sup> APAR) in sub-tropical India (Patel *et al.*, 2011). For  $C_4$  crops, value of the  $\epsilon^*$  (1.64 g C MJ<sup>-1</sup> APAR) was adopted from EC based studies on maize in arid and semi-arid china (Wang *et al.*, 2010). Effect of spatial heterogeneity of  $C_3$  and  $C_4$  crops on maximum LUE for each

pixel was also taken into account by weighting of single maximum LUE of C<sub>3</sub>/C<sub>4</sub> crops by proportion of C<sub>3</sub> and C<sub>4</sub> crops as well as native grasslands (Ramakutty and Foley, 2000) in each 5 minute grid uniformly. Finally maximum  $\epsilon^*$  each 1km pixel of cropland was obtained as :

$$\epsilon^* = \text{LUE}_{C_3} \times \text{prop}_{C_3} + \text{LUE}_{C_4} \times \text{prop}_{C_4} + \text{LUE}_{\text{grass}} \times \text{prop}_{\text{grass}} \quad (11)$$

Where,  $\text{LUE}_{C_3}$ ,  $\text{LUE}_{C_4}$  and  $\text{LUE}_{\text{grass}}$  are maximum light use efficiency of C<sub>3</sub>, C<sub>4</sub> and grass. The  $\text{prop}_{C_3}$ ,  $\text{prop}_{C_4}$  and  $\text{prop}_{\text{grass}}$  are the fraction of C<sub>3</sub> crops, C<sub>4</sub> crops and grassland for each 1km pixel of cropland areas derived from multi-temporal SPOT-Vegetation data (Agrawal *et al.*, 2003).

Secondly,  $T_{\text{scalar}}$  needs setting of maximum, minimum and optimum temperature for photosynthetic activity of each typical vegetation type. The values of  $T_{\text{min}}$ ,  $T_{\text{max}}$  and  $T_{\text{opt}}$  for c<sub>4</sub> crops were taken as 8, 30 and 42 °C, respectively (Black, 1973; Wang *et al.*, 2010). For C<sub>3</sub> crops, we used 5.0, 40.0 and 25.0 °C for  $T_{\text{min}}$ ,  $T_{\text{max}}$ , and  $T_{\text{opt}}$  respectively (Huang *et al.*, 2008)

### 2.3 Data sets and processing

**2.3.1 Satellite data processing:** Vegetation indices such as NDVI, EVI and LSWI forms a basics time series input to drive VPM model for GPP estimation. So we acquired VGT-S10 (10-day synthesis product) of NDVI and radiometric reflectance values of blue (430–470 nm), red (610–680 nm), near-infrared (NIR, 780–890 nm), and shortwave infrared (SWIR, 1580–1750 nm) bands. The standard VGT-S10 data were obtained by selecting the VGT-S1 pixels that have the maximum Normalized Difference Vegetation Index (NDVI) values within a 10-day period. The Maximum value composite reduced atmospheric effect and cloud contamination. The VGT-S10 products are freely available to the public (<http://free.vgt.vito.be>). Data on NDVI and radiometric reflectance were acquired during a period from May 2003 – April 2004 on a global scale. A subset of all images corresponds to India were generated by using India boundary mask. For removing cloud cover effects and smoothing of time-series of NDVI, 10-day NDVI datasets were filtered using wavelet filtering algorithm. Other indices e.g. EVI and LSWI were calculated using original reflectance values at top of atmosphere considering the fact that these indices are less affected by atmospheric aerosols and increasing cloud cover.

**2.3.2 Estimation of global radiation:** The photosynthetically active radiation in present study is taken as 45% of solar radiation estimated from MDIS cloud clover observations ([www.neo.nasa.gov](http://www.neo.nasa.gov)). We have used Angstrom–Prescott formula (Angstrom, 1924; Prescott, 1940) with relative sunshine from cloud cover observations as following :

$$G = R_A (A + B * S) \quad (12)$$

Where,  $G$  and  $R_A$  represent daily total of global solar radiation ( $\text{MJ m}^{-2} \text{d}^{-1}$ ) and extraterrestrial radiation ( $\text{MJ m}^{-2} \text{d}^{-1}$ ),  $A$  and  $B$  are site specific coefficients and derived for each grid by using spatially referenced geographical coordinates and altitude (GTOPO30) as per method suggested by Bandopadhyay *et al.*, (2008). Sum of  $A$  and  $B$  together represents atmospheric transparency index (ATI).  $S$  is relative sunshine index ( $S = n/N$ ) and is estimated from monthly cloud cover observations.

**2.3.3 Meteorological and ancillary data:** Daily meteorological data particularly air temperatures (Maximum and minimum temperatures) at 1-degree grid were obtained from National climate data centre, IMD. This interpolated grids of temperature derived from network of weather stations in India (Rajeevan *et al.*, ). Location of major cropping pattern was decided based on pre-dominant district of individual cropping (Atlas of Cropping System, PDCSR, ICAR, India). The profile of GPP and NPP for major cropping system extracted by taking 3×3 pixel in the centre of district having pre-dominance of cropping system.

Carbon uptake from cropland was also independently estimated from annual crop production data at district level. These cropland statistics were downloaded from website of Ministry of Agriculture ([www.mof.gov.in](http://www.mof.gov.in)). The crop statistical data are compiled for various districts. Analysis of data was restricted to 20 major crops grown with criteria of crop being included if area more than 10 thousand hectares in each state. Many steps were followed to convert harvestable product into NPP at district level. These includes conversion of unit of harvestable product into common unit of grams and then converted to NPP by using values of moisture content (MC) and harvest index (HI, ratio of harvestable produce to total plan dry weight) and root:shoot ratio ( $R_{rs}$ ) of crops obtained from published literature over India. The present study also assumes that 45% of crop biomass is C and above ground biomass accounts 80% of total crop biomass (Lobell *et al.*, 2002). The crop land NPP is thus expressed as gram C per unit area and is calculated as (Lobell *et al.*, 2002). Lower and upper estimates of ground-based cropland NPP over India for 2003-04 estimated by taking  $HI \pm SD$  and  $R_{rs} \pm SD$ .

## 3. RESULTS AND DISCUSSION

### 3.1 Spatial pattern of primary productivity

Information on primary productivity on a high-resolution grid assumes significant importance in identifying appropriate agricultural practices of carbon sequestration. In this context, VPM model run over croplands in India on 1km grid using decadal forcing, and pattern of both gross and net productivity (GPP & NPP) on annual-scale is presented in figure 1.

Spatially, the patterns of GPP and NPP have similar fashion, and hence reveal a close dependence of NPP on GPP as compared to climate that controls autotrophic respiration. On annual basis, both the GPP and NPP have showed large spatial variability. Gross and net primary productivity over croplands in India ranged from 200 – 1500 and 50 – 1000  $\text{g C m}^{-2}$ , respectively. Annual modeled NPP of cropland was ranged from very little (50  $\text{g C m}^{-2}$ ) to considerably as high as 1000  $\text{g C m}^{-2}$  over India. In general, cropland areas in Trans-Gangetic and upper Indo-Gangetic plains have predominantly high magnitude of both GPP ( $>1000 \text{g C m}^{-2}$ ) and NPP ( $> 600 \text{g C m}^{-2}$ ) followed by agricultural areas in Eastern Ghats of India. High levels of carbon uptake by agro-ecosystems in these plains and Eastern Ghat was mainly attributed to alluvial fertile soils and intensive agriculture practiced with adequate irrigation and fertilizer inputs. However, cropland in desertic tracts and some parts of dry-lands in peninsula had lower values of annual GPP and NPP. Less productivity in these regions occurred because cultivation in these areas have large dependence on rains which in turn results into reduction in both cropping intensity and per unit area productivity. Regionally, croplands in

India have significant contribution to carbon storage by terrestrial biosphere in India. Total GPP and NPP modeled by VPM over vast croplands in India amounts to 1.34 Pg C and 0.859 Pg C, respectively. The estimates of cropland NPP from VPM was found to be higher than ground-based cropland NPP (0.61 – 0.70 Pg C) due to contribution of grasses, fallow land and weeds to NPP at 1km pixel. If extreme outliers by 5 percentile on both side of NPP excluded, the modeled total cropland NPP become close to 0.7 Pg C and cropland area matches with net-sown area ( 1.46 m ha) The mean GPP and NPP was in the tune of 807 and 515 g C m<sup>-2</sup>, respectively. The contribution of croplands is more than half of total NPP of terrestrial biosphere reported in India and agrees well with the cropland NPP estimates from CASA for the same year (Nayak *et al.*, 2010).

highest magnitude of GPP. Peak GPP during kharif occurs in sugarcane–wheat system (western UP) and same occurred in rice–wheat system (Punjab) during Rabi season. Sugarcane-wheat system in western UP had the highest annual GPP (1295 g C m<sup>-2</sup>) because of longer persistence of high magnitude of GPP (60 g C m<sup>-2</sup> 10day<sup>-1</sup>) in sugarcane due to C4 photosynthesis mechanism and longer duration of active growing season.

The cropping systems, however, in semi-arid areas have comparatively less magnitude of GPP throughout the growing season. The crop rotations such as groundnut-wheat in Junagadh, Gujarat and maize-wheat in Udaipur, Rajasthan had two peaks but little less GPP on annual scale. In eastern state, triple crop system such has rice-vegetable-rice in west-bengal had three distinct peaks of GPP but the magnitude of GPP during each crop growing season was considerably less

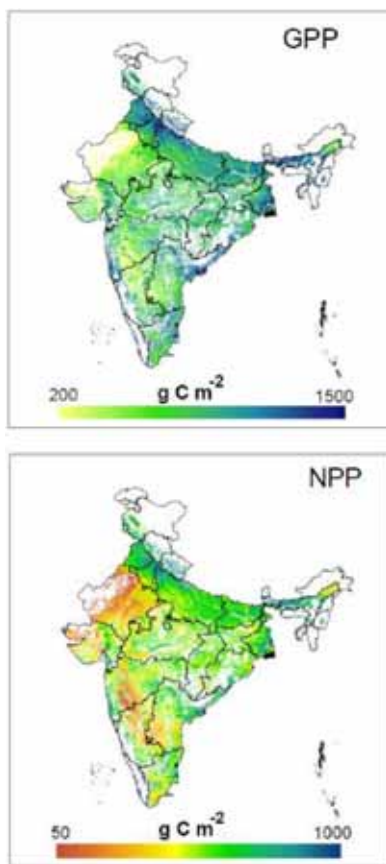


Fig.1. Spatial pattern of annual primary productivity over cropland in India during 2003-04 from VPM

### 3.2 Temporal pattern of GPP over major crop rotations

Time-evolution of carbon uptake in agro-ecosystem differs from natural ecosystems and is a key to understand influence of phenology, environmental and cropping practice such as crop rotation and C4/C3 crop mixture. Henceforth, the time-series of modeled GPP on decadal time scale extracted for various crop rotation practiced dominantly in selected districts and presented in figure 2a & b. Well managed agro-ecosystems in Trans-Gangetic and upper Indo-Gangetic plains had two distinct peaks with

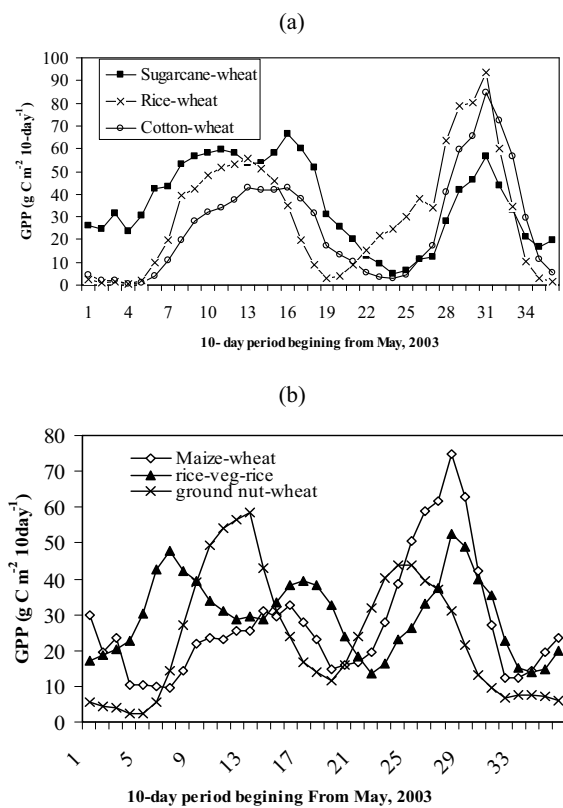


Fig. 2 Temporal variation in GPP over major cropping during 2003-04 growing season in India

### 3.3 Temporal pattern of mean cropland NPP

Net primary productivity by area-weighted average over all cropland pixels for each 10-day period had distinct time-variation over a growing season (Fig. 3). Time plot of NPP over a agricultural year illustrates that cropland ecosystem as a whole in country have two distinct active growing season as reflected from two peaks of NPP. The peaks were of same magnitude during both *kharif* and *rabi* seasons. In initial dekads of dry summer in May, the NPP was almost static and negligible. As the south-west monsoon commences, NPP increases rapidly following active growth of crops in *kharif* season and attained a peak (25 g C m<sup>-2</sup> 10day<sup>-1</sup>) in the first dekad of October, 2003. NPP then declined

steadily due to maturity and crop senescence till 22<sup>nd</sup> dekad in a year. The NPP was found to remain constant around  $15 \text{ g C m}^{-2} 10\text{day}^{-1}$  during periods of December. The NPP in *rabi* season showed remarkable increase from January and reached to peak in mid of February and decline drastically from March onwards due to harvest of crops.

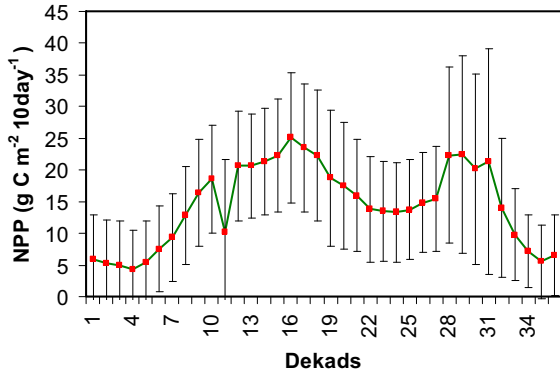


Fig. 3. Seasonal variation in modeled estimates of mean NPP over cropland in India. Bar shows  $\pm$  standard deviation

### 3.4 Validation of cropland NPP

An evaluation of our results is difficult because of the lack of ground data representative biomass measurements at 1km resolution as well as footprint scale eddy covariance measurements. Despite these limitations, modeled performance was evaluated using agricultural census data. Crop NPP modeled using VPM was compared against ground based NPP at district falling in arid, semiarid and sub humid climatic setting. A 1:1 plot (Fig. 4) showed that cropland NPP from VPM was in close agreement with ground-based crop NPP at district level for northwest India ( $R^2 = 0.63$ ). The root mean square error associated with modeled NPP was  $110 \text{ g C m}^{-2}$ .

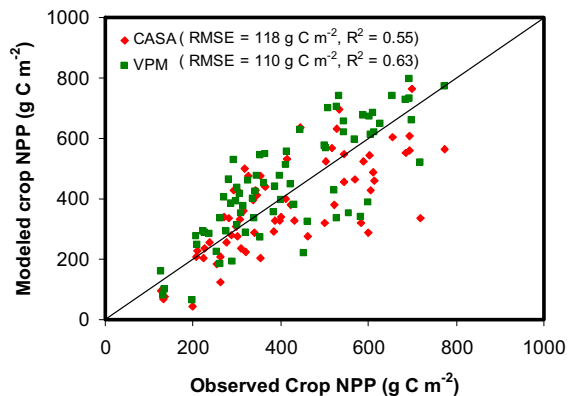


Fig. 4. Comparison of modelled cropland NPP against ground-based NPP

The present study also revealed that VPM model with more inputs from satellite could yield similar or improved estimates of cropland NPP over that of previously published estimates of CASA ( $R^2 = 0.55$ ,  $RMSE = 118 \text{ g C m}^{-2}$ ). The reason may be the accurate capture of water related constraints on NPP by satellite

based land surface wetness index in areas of irrigated agriculture. The results on NPP estimates commensurate with previous reports (Lobell *et al.*, 2002) which reveals that regions with irrigation practices may not be modeled accurately since environmental stresses predicted by meteorological conditions is not ideally applied to irrigated agriculture. When comparison made over predominantly sub-humid region comprising districts of Uttarpradesh and Haryana, the modeled cropland NPP had relatively weak agreement with ground based cropland NPP ( $R^2 = 0.35$ ,  $RMSE = 128 \text{ g C m}^{-2}$ ).

## 4. CONCLUSIONS

The present study explores potential of VPM model for estimating GPP and its seasonal dynamics over agro-ecosystems in sub-tropical environment. The VPM model seems applicable to Indian subcontinent having large area of croplands and predominantly arid-semi arid climatic regimes. The VPM model with more rely on satellite inputs such as vegetation indices (NDVI, LSWI), cloud cover based radiation, temperature and maximum light use efficiency ( $\epsilon^*$ ) parameter for individual crop species or crop group is capable for estimating regional GPP. Estimation of GPP from with simple formulation of autotrophic respiration could yield satisfactory estimates of net primary productivity over croplands. Although modeled NPP agrees well with large area estimate of crop NPP based on crop yields, Validity of VPM based GPP/NPP for particular crop rotation needs to be investigated using flux-tower measurements. Future research shall attempt to validate the capability of the VPM model in capturing the inter-annual GPP variations and interaction with environmental variables.

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#### ACKNOWLEDGEMENT

This work was carried out as a part of National Carbon Project (NCP) and supported by ISRO-Geosphere-Biosphere Programme. We thank Dr RR Navalgund, chairman PMB and Dr V. Jayraman, former Director NRSC for providing full support and encouragement to execute work.