ESTIMATION OF INDIAN AGRICULTURAL PRODUCTIVITY BASED ON PRODUCTION EFFICIENCY MODEL

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ABSTRACT:

Production Efficiency Model (PEM) being used to evaluate Net Primary Productivity (NPP) requires decomposition of productivity into independent parameters involved in the production built up process. PEM has been used for the estimation of NPP of the natural vegetation but in a first attempt of its kind it was used to estimate agricultural productivity for Indian territory. The study involved mainly three steps, (i) identification and mapping of agricultural areas (ii) estimation of agricultural production and (iii) analyses of annual and interannual variations in agricultural productivity.
The agricultural areas were identified and mapped using NDVI-Climatological modeling technique. NASA/NOAA Pathfinder AVHRR Land (PAL) 10 day composited NDVI data with a spatial resolution of 8 km was used for the study. The agricultural pixels were identified as outliers in the NDVI-rainfall relationship developed using annual integrated NDVI and annual rainfall data for the year 1989. An irrigated agricultural areas map was generated using the value of these pixels.
The NDVI data for the years 1987, 1988, 1989 was used to estimate fraction of PAR absorbed (fAPAR) based on the relationship fAPAR = -0.31+1.39*NDVI provided by the SAIL model. Incident PAR (IPAR) data set for India was extracted from the monthly global IPAR data set already generated using UV reflectivity data from Nimbus Total Ozone Mapping Spectrometer (TOMS). The IPAR data when combined with the fAPAR data, provided absorbed PAR (APAR). Assuming the irrigated agricultural areas mapped above as constant over the three years period, the agricultural APAR was extracted using the irrigated agricultural areas mask. Agricultural APAR was subsequently converted to agricultural NPP using the mean conversion efficiency (ϵ) value of 2.07 calculated for cultivations based on literature survey. The agricultural NPP was finally converted to economic yield based on the area weighted average harvesting index of various crops grown in India. The annual and interannual variation in agricultural productivity of India have been discussed vis-a-vis reliability of the model for these studies.

1. INTRODUCTION

Intenational Geosphere Biosphere Program (IGBP, 1992) envisaged creation of improved global data sets to properly evaluate the environmental changes occuring on regional and global scales. Frequent availability of remote sensing data through various satellites have now made it possible to get better estimates of carbon fixation and terrestrial productivity on earth. Various estimates for global net primary productivity has been made with rather large discripancies between the estimates (Ruimy et.al. 1994). Better techniques, therefore, needs to be developed for making reliable estimates of productivity.

Agricultural productivity with its fundamental role in food supply has been the obvious focus. Due to its dependence on various external factors and the attendant uncertainties, large regional disparities exist in the agricultural production which needs to be properly evaluated for global planning. Studies on productivity usually focus on two aspects:
(a) To predict the crop production of a certain year before harvest using simple statistical models. Models used for this purpose, specially Spectral Indices-Yield Regression models (Dubey et.al. 1994), are usually developed for a certain kind of crop in a small region and have strong dependence on

local characteristics.
(b) To evaluate net primary productivity (NPP) to provide spatial information that can be used for land use planning using more recently developed and sophisticated Production Efficiency Model (PEM).

PEM which can also use remotely sensed data as inputs, has been successfully used for estimation of global NPP (Prince and Goward 1995), but no separate estimates for agricultural productivity has yet been attempted on a regional and global scale. Therefore, agricultural productivity estimation was taken up for India, one of the agriculturally dominant country, using PEM.

2. Theory

Productivity is the rate of atmospheric carbon uptake by vegetation through the process of photosynthesis. Built up of productivity is a complex phenomenon which is a culmination of many temporal plant processes. Recent methods to evaluate NPP involves decomposition of productivity into independent parameters such as incoming solar radiation, radiation absorption efficiency and conversion efficiency of absorbed radiation into organic matter (Kumar and Monteith, 1981). The models developed in these studies are an advancement over the statistical models properly accounting for various steps in the productivity built up process.

Goward et.al.(1985) showed that vegetation indices, such as Normalized Difference Vegetation Index (NDVI) are related to net primary production (NPP, g m^{-2} $year^{-1}$). Monteith (1977) suggested that NPP under non-stressed conditions is linearly related to the amount of photosynthetically active radiation (PAR, MJ m^{-2}) that is absorbed by green foliage (APAR, MJ m^{-2}). Further, Kumar and Monteith (1981) showed how the fraction of PAR absorbed (fAPAR) relates to the ratio of red reflectance (R) to near infrared (NIR). Asrar et.al. (1984) subsequently related the NDVI to the fAPAR; hence NDVI may be used to estimate NPP at global scale by the relationship:

$$NPP=\epsilon\Sigma(APAR)=\epsilon\Sigma(NDVI*IPAR)$$

where Σ(APAR) is the annual sum of APAR, ϵ is the PAR conversion efficiency (g MJ^{-1}) and IPAR is the incident PAR. This is the simplest form of the Production Efficiency Model (PEM).

Eck and Dye (1991) described a simple, physically based, satellite remote sensing method for estimating IPAR that uses ultraviolet (UV) reflectivity data from the Nimbus Total Ozone Mapping Spectrometer (TOMS). Subsequently, Dye (1995) generated a time series global monthly IPAR data set using the same technique, which is quite useful for regional and global productivity studies (Prince and Goward, 1995). Dye and Goward (1993) also created a global APAR image using spectral reflectance measurements from the NOAA-7 AVHRR and TOMS data.

One of the major problem in the NPP estimation is the finding of representative values of ϵ for various vegetation types as it changes with the type of vegetation, temperature, water availability and metabolic type of the plant (C_3 or C_4 type). Prince 1991 and Ruimy et. al. (1994) searched through the literature and listed ϵ values for various vegetation and ecosystem types. Hunt (1994) suggested that global estimates of NPP based on vegetation indices should include a classification among established forest, young forest and non-forest ecosystems to account for differences in ϵ.

3. DATA

3.1 Satellite data

3.1.1 NDVI data: NASA/NOAA Pathfinder AVHRR Land (PAL) 10 day composited NDVI data set for the year 1987, 1988, and 1989 was procured from the Goddard Distributed Active Archive Center (DAAC), USA. To generate composited data set, 10 consecutive days of data are combined, taking the observation for each 8 km bin from the data with the fewest clouds and atmospheric contaminants as identified by the highest NDVI value. There are three composites per month for each year of data. The compositing technique fairly removes the cloud contamination from the data to use in climatic modeling studies (Agbu and James, 1994). The data is available on Goode's Equal Area Projection.

3.1.2 IPAR data: Global IPAR data set generated by Dye (1995) using UV reflectivity data from Nimbus TOMS sensor through the method of Eck and Dye (1991) was used for the present study. This TOMS IPAR data set consists of monthly average estimates, at a spatial resolution of 1°*1° degree from 66°N to 66°S latitude. The data for the Indian region was extracted from the global data set and interpolated to match the 8 km resolution of NDVI data.

3.2 Climatic data

Time series climatic data for India including daily rainfall, maximum and minimum temperature were extracted from Global Summaries prepared by National Climatic Data Center, USA. This contained daily observations for more than 200 stations of India for 1977-1991. But complete data for only about 75 stations in India was available for the year 1989 which was used in the present study. The daily data was converted to monthly rainfall and monthly average mean temperature.

4. MAPPING AGRICULTURAL AREAS:

One of the major challenge faced in the estimation of agricultural productivity is the mapping of agricultural areas. Therefore, efforts were made to develop an automated technique for the identification and mapping of agricultural areas based on NDVI-climatological modeling. The concept is based on the fact that the NDVI of the natural vegetation is expected to show a positive correlation with the climatic factors of the area, but not the NDVI of the agricultural crops which are artificially managed by supplying additional inputs in terms of water and nutrients. Therefore, there is a possibility of identifying the agricultural pixels as outliers in the NDVI-climatological relationship (Hooda and Dye, 1995).

The NDVI and climatic data for the year 1989, a normal year with respect to monsoon effecting Indian agriculture, was used for the present study. The point climatic data for about 75 meteorological stations was correlated against the average NDVI in a 3*3 pixel window around the same location. Relationship was tried for different crop growing seasons of winter, summer and monsoon as well as on annual basis.

No relationship between NDVI and mean temperature could be observed in the present study. The possible reason could be that India is a tropical country and temperature is not a limiting factor for the growth of vegetation for most of the year. Relationship between NDVI and rainfall in different seasons also could not be observed but the annual integrated NDVI did show a logarithmic relationship with the annual rainfall. However, some outlier pixels showing very high NDVI at low rainfall were also noticed. The relationship improved significantly after removing these outlier pixels. Based on this analysis a pixel was classified as agricultural pixel if,

$$\Sigma NDVI = 0.0042 * \text{ann. rainfall} + 0.5$$

Since this technique identifies high NDVI pixels at low rainfall, it would be logical to assume these pixels as irrigated agricultural pixels because only irrigated crops can show high NDVI even at low rainfall due to availability of water through irrigation. Thus, one of the limitations of the technique is that it may not separate out dry land agricultural areas as well as some of the irrigated areas in the high rainfall eastern region of the country. However, when compared with the available irrigated areas map of the country, the technique seems to give a fair idea of the major irrigated areas in the country. The net irrigated area reported in the country is only 397290 sq. km., but the net sown area with reasonably assured water supply is reported as 726170 sq. km. (Anonymous, 1987) compared to 750016 sq. km. observed based upon the present technique. Thus, the NDVI-climatological technique proved quite useful in quickly generating an irrigated agricultural areas map. This map was used as a mask to extract different data sets for only agricultural areas of India.

5. AGRICULTURAL PRODUCTIVITY ESTIMATION

Use of PEM for estimating productivity involves different steps as detailed below:

5.1 Fraction of IPAR absorbed by vegetation (fAPAR)

The spectral vegetation index measurements produced by calculating the NDVI have been shown, empirically and theoretically, to be related to fAPAR in vegetation canopies (Ruimy. et.al., 1994). Although there are several possible limitations to such an inference, it does appear that an approximation of this fAPAR can be derived from the NDVI (Myneni and Williams, 1994). Ruimy et.al. (1994), after an extensive search through the literature, tabulated various relationships between fAPAR and NDVI developed by different workers. For the present study relationship based on SAIL model simulation was used which is represented as:

$$fAPAR = -0.31+1.33*NDVI$$

The 10 day composited NDVI data was first averaged to give average monthly NDVI for all the three years. Calibrations for negative values on land in the NDVI data were made in way to set the bare soil fAPAR to zero. This calibration required a uniform enhancement of 0.1 NDVI units in the data. From average monthly NDVI, fAPAR for each month was calculated using the above equation.

5.2 Absorbed Photosynthetically Active Radiations (APAR)

The APAR calculations required IPAR and fAPAR data sets for India. Monthly fAPAR data set of India for the three years was generated as described in the previous step. The monthly Indian IPAR data extracted from TOMS global data set of Dye (1995) was combined with the respective fAPAR data to give monthly APAR in MJ m^{-2}. Assuming the agricultural areas mapped above as constant for all the three years, the agricultural APAR was extracted using the agricultural areas mask already generated.

5.3 Agricultural NPP, biomass and production

Agricultural NPP is defined in the present study as the dry matter (both above ground and below ground) produced per unit agricultural area and biomass as the total dry matter produced. Production is defined as the dry matter partitioned into economic yield.

The conversion of APAR into productivity requires conversion efficiencies of APAR into dry matter (ϵ) of various crops. Since we had only an agricultural areas map where different crops are not identified, therefore, a mean conversion efficiency value for all the cultivations is required for use in the model. Ruimy et.al (1994) conducted an extensive literature survey and tabulated the ϵ values for different types of vegetation reported by different workers. But most of the workers reported ϵ values in terms of above ground dry matter only. To overcome this problem they also searched through the literature to estimate a mean ratio of below ground NPP to above ground NPP and arrived at a value of 0.24 for cultivations. Based on this factor they arrived at a mean ϵ value of 2.07 g dry matter (above ground and below ground) MJ^{-1} of APAR for cultivations for converting APAR data into NPP. This value was used for converting APAR data into agricultural NPP and biomass in the present study.

The biomass can be converted to agricultural production using the Harvest Index (HI) values of various crops. HI values for major summer and winter crops, locally known as Kharif and Rabi crops, respectively, were collected through literature survey. An area weighted average HI for summer and winter season crops was calculated as 0.275 and 0.279, respectively. These values were used to calculate the monthly production from monthly NPP.

5.4 Annual and Interannual variations in biomass and production

The monthly agricultural NPP and biomass produced in the Indian territory as calculated using the above steps are shown in table 1. The NPP and consequently biomass starts building up in January after the sowing of winter season crops in December. It reaches its peak in the month of February/ March due to peak vegetative growth of the crops and then drops suddenly in April due to harvesting of winter crops. The biomass generation remains low in the summer months of May and June and again starts building up in July/August due to onset of monsoon and growth of summer crops. This again reaches its peak in September/October and then falls suddenly in November due to harvesting of summer crops. Sowing of winter season crops starts in the end of November or December and therefore, the biomass remains low

Table 1. Estimates of agricultural NPP and biomass for India.

Months	NPP ($Q\ ha^{-1}$)			Biomass (Million tons)		
	1987	1988	1989	1987	1988	1989
1	3.67	4.82	7.11	27.55	36.14	53.36
2	6.90	6.10	8.98	51.73	45.75	67.33
3	6.56	6.57	8.87	49.18	49.58	66.49
4	3.47	2.14	6.03	26.02	16.15	45.21
5	3.94	4.31	3.33	29.58	32.54	24.94
6	4.52	3.55	3.57	33.93	26.79	26.79
7	3.32	2.62	4.67	24.89	19.77	35.00
8	6.52	7.92	7.59	48.90	59.83	56.94
9	8.19	10.05	11.63	61.45	76.88	87.23
10	7.67	8.42	11.81	57.56	63.58	88.57
11	4.89	6.28	6.29	36.67	47.40	47.15
12	3.69	5.28	4.55	27.67	39.86	34.15
Annual	58.68	62.75	83.12	470.13	514.27	633.16

during these months. Thus the PEM seems to describe correctly the annual variations in agricultural biomass generation.

Agricultural NPP of 58.68, 62.75 and 83.12 $Q\ ha^{-1}$ and biomass of 470.13, 514.27 and 633.16 million tons was estimated for the years 1987, 1988 and 1989, respectively. This biomass was translated into 136.31, 147.56 and 181.16 million tons of agricultural production for the above three years.

The performance of monsoon is the critical factor in Indian agriculture as it is the single most important factor effecting agricultural productivity. A study in the behavior of Indian monsoon showed that it was normal for the year 1989. But it showed a negative anomaly during 1987 and a positive anomaly during 1988 causing drought and floods in the two years, respectively. Therefore, the crop growth and agricultural productivity was drastically reduced in both the years. This interannual anomaly in agricultural productivity could also be described through the present methodology using PEM. The highest agricultural production of 181.16 million tons was estimated for the year 1989 as compared to 136.31 and 147.56 million tons for the years 1987 and 1988, respectively.

We made an effort to compare the estimated agricultural production figures with the reported figures from Bureau of Economics and Statistics (BES). But we find it difficult to compare the figures because the estimated values are an integration over the calender year whereas the BES reported figures are as per the agricultural year i.e. starting from summer crops in June/July and ending with the harvesting of winter crops in April in the next calender year. However, the general trends of agricultural production compares fairly well with the reported figures.

6. CONCLUSIONS

Based upon the present study it could be concluded that the NDVI-Climatological modeling technique developed provided an automated and quick way to map irrigated agricultural areas in India. It was possible to make fairly correct estimates of agricultural production for India using the PEM. The model was also able to describe the annual and interannual variations in agricultural production of India. Therefore, the technique developed in the present study seems to have a great potential for estimating agricultural production more accurately.

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REFERENCES

Agbu, P.A. and James, M.E. 1994. The NOAA/NASA Pathfinder AVHRR Land data set User's Manual. Goddard Distributed Active Archive Center, NASA, Goddard Space Flight Center (GSFC), Greenbelt. USA.

Anonymous, 1987. A social and economic atlas of India. Oxford Press, Delhi.

Asrar, G., Fuchs, M., Kanemasu, E.T. and Hatfield, J.L. 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agron. J., 76:300-306.

Dubey, R.P., Ajwani, N., Kaluburme, M.H., Sridhar, V.N., Navalgund, R.R., Mahey, R. K., Sidhu, S.S., Jhorar, O.P., Cheema, S.S. and Narang, R.S. 1994. Pre-harvest wheat yield and production estimation for Punjab, india. Int. J. Remote Sens. 15: 2137-2144.

Dye, D.G. 1995. Intercomparison of global PAR data sets. Geophys Res.Lett. Submitted.

Dye, D.G. and Goward, S.N. 1993. Photosynthetically active radiation by global land vegetation in August 1984. Int. J. Remote Sens., 14:3361-3364.

Eck, T.F. and Dye, D.G. 1991. Satellite estimation of Incident Photosynthetically Active radiation using ultraviolet reflectance. Remote Sens. Environ. 38: 135-146.

Goward, S.N., Tucker, C.J. and Dye, D.G. 1985. North American vegetation patterns observed with the NOAA-7 Advanced Very High Resolution Radiometer. Vegetatio, 64: 3-14.

Hooda, R.S. and Dye, D.G. 1995. Identification and mapping of irrigated vegetation using NDVI-Climatological modeling. Proc. Asian Conf. Remote Sens., 20-24 November 1995, Nakhon Rachasima, Thailand. pp. Q-9-1 - Q-9-6

Hunt, E.R.Jr. 1994. Relationship between woody biomass and PAR conversion efficiency for estimating net primary production from NDVI. Int. J. Remote Sens. 15: 1725-1730.

IGBP, 1992. Improved global data for land applications. International Geosphere Biosphere Program, IGBP Secretariate, Stockholm, Sweden. Report no. 20.

Kumar, M. and Monteith, J.L. 1981. Remote sensing of crop growth. In: H. Smith (ed.), Plants and the daylight spectrum. Academic Press, London, pp. 133-144.

Monteith, J.L. 1977. Climate and efficiency of crop production in Britain. Phil. Trans. Royal Soc. London, B 281: 277-294.

Myneni, R.B. and Williams, D.L. 1994. On the relationship between FAPAR and NDVI. Remote Sens. Environ. 49: 200-211.

Price, S.D. 1991. A model of regional primary production for use with course resolution satellite data. Int. J. Remote Sens. 12: 1313-1330.

Prince, S.D. and Goward, S.N. 1995. Global primary production: a remote sensing approach. J. Biogeography, 22: 2829-2849.

Ruimy, A., Saugier, B. and Dedieu, G. 1994. Methodology for estimation of terrestrial net primary production from remotely sensed data. J. Geophy. R. 99: 5263-5283.