GROWING ENVIRONMENT CHARACTERIZATION OF RICE AND YIELD PREDICTION USING TIME COMPOSITED NOAA AVHRR OPTICAL AND THERMAL DATA

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ABSTRACT:

Relative (actual / potential) evapotranspiration (RET) was derived using ten-day composite NOAA PAL datasets (8km x 8km spatial resolution) over Indian landmass and an operational energy balance algorithm for five agricultural years (June-May) between 1996 to 2001. This was used to characterize 'Kharif' (June-October) rice growing environment and its yield prediction in rainfed conditions. Inverse correlation (r = 0.6 to 0.75) was found between RET and Keech-Byram meteorological drought index (KBDI) only in rainfed rice growing regions but least correlation (r = 0.4) was found in irrigated rice growing region. Substantial reduction in RET was also found in a sub-normal (2000) than normal (1999) monsoon season for rainfed rice growing regions only. RET based crop response factor (Ky), averaged from three intermediate years (1997, 1998, 1999) for five different durations within growing period, varied between 0.9 to 1.4. The RET based yield prediction at district level for Kharif 1996 and 2000 in Madhya Pradesh state produced root mean square (RMS) error in the order of 34.4 to 47.5 percent of observed mean. The sources of errors suggest the use of diurnal observations from geostationary sensors at relatively finer spatial resolution and crop simulation model at potential level for better yield prediction.

1. INTRODUCTION

The assessment of in-season variation of growing environment and the study of its effect on agricultural outputs such as biomass and yield, are required for regular agricultural monitoring. Rice is the first staple food worldwide including India. It is grown in a wide range of agroclimatic conditions (Yoshida, 1981; Ladha *et al*, 2000) as rainfed or irrigated, direct seeded or transplanted, in extreme cold to warm climates in summer, rainy, autumn and winter seasons. Its productivity is most vulnerable to early, middle and late season stresses during its growing period (Bouman and Toung, 2000; Mahmood *et al*, 2003; Sharma, 1989; Wopereis *et al*, 1996). So, the assessment of its production information depends on the monitoring of inter and intra seasonal fluctuations of growing conditions.

Evapotranspiration process is linked to crop growth process such as photosynthesis (Giardi *et al*, 1996). Stresses arising from nutrient, water deficiencies or infestation of pests and diseases reduce evapotranspiration (Polley, 2002). Actual evapotranspiration (AET) as a fraction to its potential (PET) can be used to assess the deviations from potential crop water demand and growing conditions.

Various spectral and thermal indices such as NDVI (normalized difference vegetation index), VCI (vegetation condition index), TCI (temperature condition index) were formulated using either narrow optical or thermal bands data from satellite observations for evaluation of vegetation health and productivity (Kogan *et al*, 2003; Singh *et al*, 2003). Spectral yield models were also developed using single or multi-date normalized difference vegetation index (NDVI) (Quarmby *et al*, 1993) or vegetation condition index (VCI) (Hayes and Decker, 1996) with coarser resolution remote sensing data. These statistical models based on spectral indices could explain only upto 55 percent yield variability. Recently, combination of Land Surface Temperature (LST), NDVI and soil moisture from coarse resolution data (≥ 8km) were used to develop statistical yield models to predict IOWA state wheat and soyabean yield (Prasad *et al*, 2006).

The relative evapotranspiration, RET (AET / PET), is direct physical input as stress factor to crop water productivity functions and yield modelling (Doorenbos and Kassam, 1979). RET derived from Meteosat geostationary sensor could explain yield variability to the extent of 70 – 94 percent for maize in Africa and Europe (Robeling *et al*, 2004) at national scale. In present study, relative evapotranspiration (RET) was derived from time series of NOAA Pathfinder AVHRR land (PAL) data sets (8km x 8km spatial resolution) using a modified EARS (Environmental Applications and Remote Sensing, Netherlands) operational energy balance algorithm, to characterize rice growing environment and predict its yield.

2. DATA SETS

NOAA Pathfinder AVHRR land (PAL) data of India subsets (68^0 –100^0E, 5^0-40^0 N) from Asia continental datasets between June 1996 to April 2001 were used. These correspond to five crop growing periods of rainy season, called 'kharif' and winter season, called 'rabi', the terms commonly used in almost all parts of India (ICAR, 2000) except Tamil Nadu state. The 'Kharif' generally extends from June to October or upto November in some regions. The 'rabi' season generally spans over November or December of

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preceeding year to April or May of subsequent year. These two ‘crop growing seasons’ generally constitute an ‘agricultural year (June to May)’.

Though the datasets were generated for the period 1981 and 2001, the continuous time series over Asia is available (*ftp://disc1.gsfc.nasa.gov /data/avhrr/global_8km/*) between 1996 to August 2001 only. The datasets are ten-day composites having least cloud contamination with a spatial resolution of 8km x 8km in Goodies homosoline projection with geolocation accuracy of better than one pixel. There are three ten-day composites in each month numbered as June1, June2, June3, …….., May1, May2, May3 and twelve parameters generated in scaled numbers (byte / integer) in each ten-day composite. The listing of parameters and gain-offsets for their conversion to actual values is given by Agbu and James (1994). Eight out of twelve parameters, normalized difference vegetation index (NDVI), cloud cover flag (clavr), time of overpass (TOP), solar zenith angle (sza), red reflectance (Ch1), near infrared reflectance (Ch2), thermal infrared brightness temperatures (Ch4 and Ch5), were then plugged into energy balance algorithm to generate relative evapotranspiration (RET). The temporal smoothening of reflectance, brightness temperatures and NDVI across cloudy events was made on spatial scale using HANTS (Harmonic Analysis of Time Series) software (Verhoef *et al*, 1996; Roerink *et al*, 2000).

Keech-Byram meteorological Drought Index (KBDI) (Keetch and Byram, 1968) was computed for Kharif season from ground measured daily air temperature and rainfall observatories of India Meteorological Department (IMD) in the proximity to four selected agroclimatically different kharif rice growing regions. But these were computed only for four kharif seasons, 1996, 1998, 1999 and 2000. The meteorological data of 1997 were not available, so KBDI could not be computed for ‘Kharif’ 1997. Detailed computational procedure is described in section 3.2.

3. METHODOLOGY

3.1 Computation of Energy balance

Relative evapotranspiration was derived following an operational energy balance algorithm developed by EARS (Environmental Applications and Remote Sensing Ltd.), Netherlands using Meteosat data. The original algorithm was described by Rosema (1993) and later on used to derive energy balance components and relative evapotranspiration at continental scales over Europe, Africa and China (Rosema *et al*, 2004). The relative evapotranspiration during crop growing season was successfully used to forecast crop yield (Robeling *et al,* 2004). The algorithm basically uses Meteosat geostationary noontime broad optical band data in 0.3 -1.1µm, and noon-midnight thermal infrared (TIR) (10.5-12.5µm) data. The flowchart for RET computation using NOAA PAL datasets is given in Figure 1. EARS algorithm estimates RET both for clear and cloudy sky conditions, but the present adaptation is for clear sky conditions only.

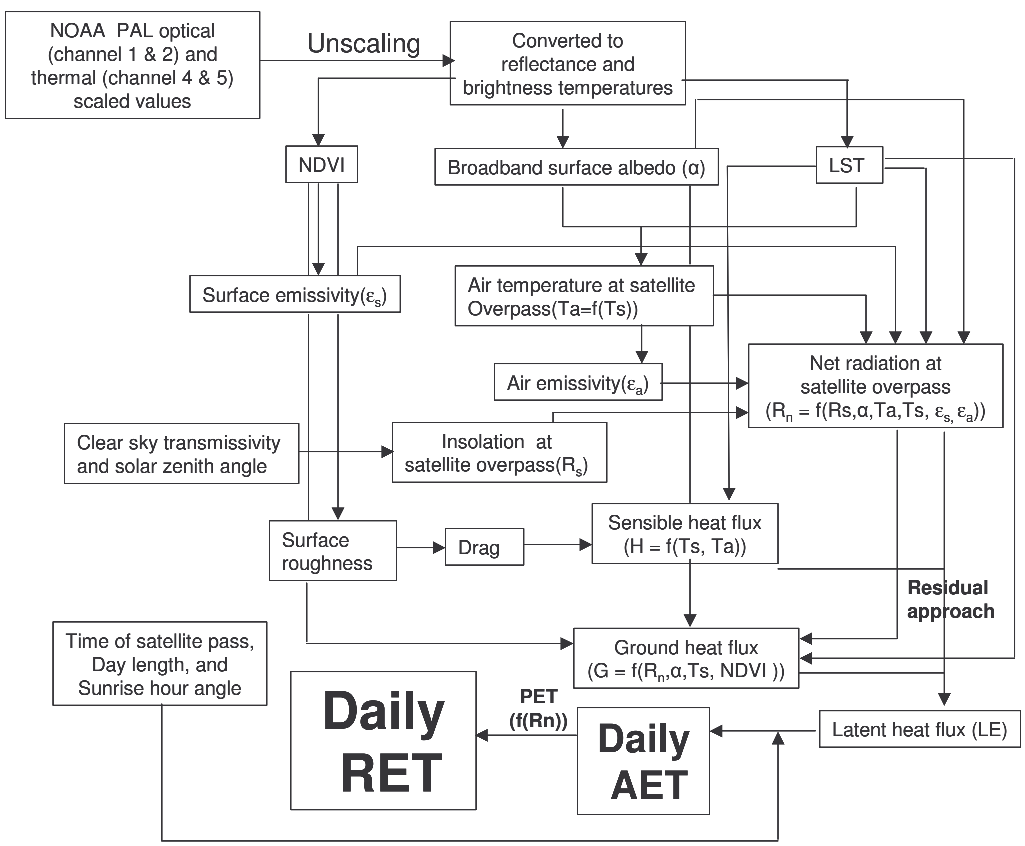

Figure 1. Computation of relative evapotranspiration in clear sky conditions using PAL datasets

3.2 Keetch-Byram Drought Index (KBDI)

This is a meteorological drought index computed from daily rainfall, maximum air temperature and mean annual rainfall. Conceptually, it describes soil moisture deficit in rainfed system only. It is defined as a number representating the net effect of evapotranspiration and precipitation in producing cumulative moisture deficiency in soil layers. This index (KBDI) has been used for over 30 years in some areas of United States and it is used currently to find out relationship with fire activity in Hawaii islands (Dolling *et al*, 2005). It was also used for drought monitoring of meteorological sub-divisions (Fujioka 1991; Heim, 2002; Johnson and Forthum, 2001).

The physical theory for the KBDI is based on a number of assumptions (Keetch and Byram, 1968). The first assumption is that soil moisture is at field capacity with a water depth equivalent of 200 mm. The second assumption is that the rate of moisture loss in an area depends on the vegetation cover in the area, and vegetation density is a function of mean annual rainfall. Hence, daily transpiration is approximated by an inverse exponential function of the mean annual rainfall. Finally, the evaporation rate of soil moisture with time is assumed to be exponential function of the daily maximum temperature.

This index was chosen to compare with PAL data derived RET that represents root zone wetness. KBDI is also simple to compute on daily basis. Its values range from 0 to 800, with 800 indicating extreme drought and 0 indicating saturated soil. The initialization of KBDI usually involves setting it to zero after a period of substantial precipitation (25 mm) at the onset of southwest monsoon in 'kharif' season. KBDI can be computed using the following equation :

$$\Delta Q = ((800 - Q)*((0.968*EXP(0.0486T) - 8.30)* \Delta t) * (0.001/(1+10.88*EXP(-0.0441M) \quad (1)$$

Where, Q is the current KBDI, T is the daily maximum temperature, M is the mean annual rainfall, Δt is a time increments set equal to one day

3.3 Rice Mask Generation

The advanced techniques of land cover classification using single date high resolution Linear Imaging Self Scanner (LISS)-III (23m) multispectral data from Indian Remote Sensing Satellite – P6 (IRS-P6) to 'full resolution' AVHRR time series data are available now days. The techniques of global land cover classification using coarse resolution satellite data have been demonstrated by Sato and Tateishi (2004) using SPOT-VGT data of 1km resolution and Hastings and Tateishi (1998) applying NOAA PAL climatological data resampled at 16km resolution. Different land cover categories were generated in present study using hierarchial decision tree classifier and temporal NDVI profiles of NOAAPAL datasets. Same classifier was used to discriminate forest, agriculture, bare and scrub lands for June 1996 to April 1997, June 1997 to April 1998, June 1998 to April 1999, June 1999 to April 2000 and June 2000 to April 2001. NDVI profile consists of monthly maximum NDVI generated from ten-day composites. Ultimately, the mask containing rice-dominated pixels of Madhya Pradesh state in India were retained for spatio-temporal analysis. The forest map published by Forest Survey of India (SFR, 1998) was used as reference guide to discriminate forest pixels. The spatial distribution of croplands derived from PAL NDVI data at 8km resolution was again cross checked with cropland mask (not shown here) derived from relatively finer resolution SPOT-VGT monthly NDVI temporal profiles generated using 1km resolution data in 1999 and 2000 applying same classifier. Over or under classification was evident with 8km resolution PAL data as compared to 1km SPOT VGT data due to mixed pixel response, but the major agricultural patches with pixels having predominant rice were quite similar in both the cases.

4. RESULTS AND DISCUSSION

4.1 Rice growing environment characterization

Four selected rice growing regions falling in north, central, southeastern and eastern part of India having differences in agroclimatic conditions were chosen for growing environment characterization. These study regions are located in the proximity of either State Agricultural Universities (SAUs) or Indian Council of Agricultural Research (ICAR) research stations such as: Punjab Agricultural University (PAU), Ludhiana ($30^0 56^/$N, $75^0 52^/$E), Jawaharlal Nehru Krishi Vidyalaya Vidyalaya, Jabalpur ($23^0 10^/$N, $79^0 57^/$E), Water Technology Centre (ICAR) research farm, Khurda ($20^0 12^/$N, $85^0 42^/$E) and Bidhan Chandra Krishi Viswavidyalaya, Kalyani ($23^0 06^/$N, $88^0 01^/$E), respectively. These are represented as NSR (northern study region), CSR (central study region), SESR (south-eastern study region) and ESR (eastern study region). The different agroclimatic parameters such as: physiography, soil, crop calendar, atmospheric thermal regime, water regime (rainfall / irrigation), nutrient management for rice crop over these study regions are given in Table 1. This clearly showed substantial differences in average rice growing environment among four, NSR with fully irrigated rice having highest fertilizer (NPK) application rates, ESR with rice grown with rainfall plus protected irrigation and low NPK application rates, SESR and CSR having rainfed rice with differences in NPK application rates.

4.2 Relative evapotranspiration and KBDI

The daily KBDI was computed using available ground measured daily rainfall and air temperature data obtained from nearest IMD meteorological observatories for 'kharif' rice season 1996, 1998, 1999 and 2000. Ten-day composites were computed from daily values. The RET averages of study regions, extracted from ten-day composites were compared with KBDI. The plots are shown in Figure 2a-d. KBDI values falling outside 0-800 were not considered because the lower and upper limits correspond to extremely wet and dry conditions, respectively.

The focus of present analysis is to investigate whether inverse correlation exists between RET and KBDI, rather than developing empirical relations between these two because of scale mismatch. The correlation (r) was least (0.42) in fully irrigated rice growing system and increased from less irrigated system (0.6) to rainfed systems at SESR (0.64) and CSR (0.75). Agricultural drought depends on water availability to crops throughout crop growth cycle. It will not show up signals during meteorologically dryspells in the areas having assured water supply from canals or ground water. Under such circumstances, RET will not be correlated to KBDI as in NSR. The correlation (r) increases with increasing dependence of water availability from rainspell as in the case of ESR (protected irrigated), SESR (rainfed), CSR (rainfed).

Parameters	Study regions			
	NSR	ESR	SESR	CSR
1. Physiography				
a) Latitude-longitude bounds	30°61' N - 30°71' N to 75°49' E - 75°59' E	23°3' N - 23°13' N to 87°46' E - 87°56' E	20°10' N - 20°20' N to 85°47'E - 85°57' E	23°7' N - 23°17' N to 80°02' - 80°12'E
b) Elevation (m) from m.s l	247	90	36	393
c) Land type	Northern plain	Eastern plain	South Eastern plain	Central plain
2. Soil				
a) Order	Alfisols	Oxisols	Ustisols	Cambisols
b) Texture	Sandy loam	Silty loam	Sandy loam	Clayey loam
3. Monsoon crop (rice)				
a) Sowing and harvesting dates	25th May-10th Oct	15th July-30th Nov	20th June –10th Nov	15 th July - 31st Oct
b) Crop growth duration (days)	138	138	140	108
c) Major planting type	Transplanted	Transplanted	Transplanted	Direct seeded
4. Thermal regime				
a) Maximum air temperature (°C)				
i) Mean	33.3	32.1	31.9	32.0
ii) Range	22.8 - 41.4	22.0 - 40.5	25.0 - 42.0	18.0 - 45.0
iii) SD	3.4	2.2	2.4	3.2
b)Minimum air temperature (°C)				
i) Mean	22.1	24.3	24.5	21.1
ii) Range	8.2 -30.6	7.5 -28.4	11.0 –29.0	3.0 - 31.0
iii) SD	6.05	3.4	3.1	4.1
5. Water regime				
a) Annual rainfall (mm)	850	1200	1570	1560
b) No. of irrigation	18	7	NIL	NIL
c) Irrigation amount (cm)	5 each	4.5 each	NIL	NIL
6.Nutrient management				
Average N: P: K application (Kgha^{-1})	120 :30 :30	21 : 38 :49	50 :20 :20	28 :28 :20

NSR = Northern study region, ESR = Eastern study region, SESR = South eastern study region
CSR = Central study region.

Table 1. Agroclimatic characteristics of four selected rice growing study regions

Relative evapotranspiration, being average soil wetness (1 – dryness), can be used as an indicator to distinguish normal and sub-normal monsoon years. The comparison between two seasonal RET variation was made (Figure 3a-d) for 'kharif' rice growing periods falling in two contrasting year 1999 (normal) and 2000 (sub-normal) as declared in drought bulletins of IMD based on rainfall distributions. RET was substantially low in rainfed systems (SESR and CSR) throughout growing period in 2000 than 1999 as compared to irrigated system (NSR). The occurrences of substantial RET reduction (> 0.2 units) were more in less irrigated rice at ESR (4 dekads) than irrigated conditions at NSR (one dekad). The irrigated rice system generally has assured water supply irrespective of rainfall occurrences. This resulted into least difference in RET between a normal and sub-normal years unlike other stations.

4.1 Yield prediction

Attempt has been made to predict rice yield in Madhya Pradesh state of India dominated with rainfed agriculture. The irrigated area in this state is about 39 percent of net sown area. The growth response of crops to water stress in relation to yield was reported by Doorenbos and Kassam (1979) after analyzing data from various crops worldwide. The relation between RET and relative yield (Ry) is given below:

$$\text{Crop response factor (Ky)} = (1-Ry)/(1-RET_t) \quad (2)$$

$$Ry = \text{Actual yield / Potential yield} \quad (3)$$

$$RET_t = \Sigma AET_t / \Sigma PET_t \quad (4)$$

t = Time in days after spectral emergence. Here, it is in dekads (days = i -th dekad after spectral emergence X 10)

PET = potential evapotranspiration computed from daily net radiation (Rn) using Priestly -Taylor (1972) formulation

Potential yield = Maximum historical district yield in a time series (Rosema *et al*, 2004) of 10 years. Here, the districtwise potential yield was determined from maximum within the time series between 1995 to 2004 (FAI, 2001).

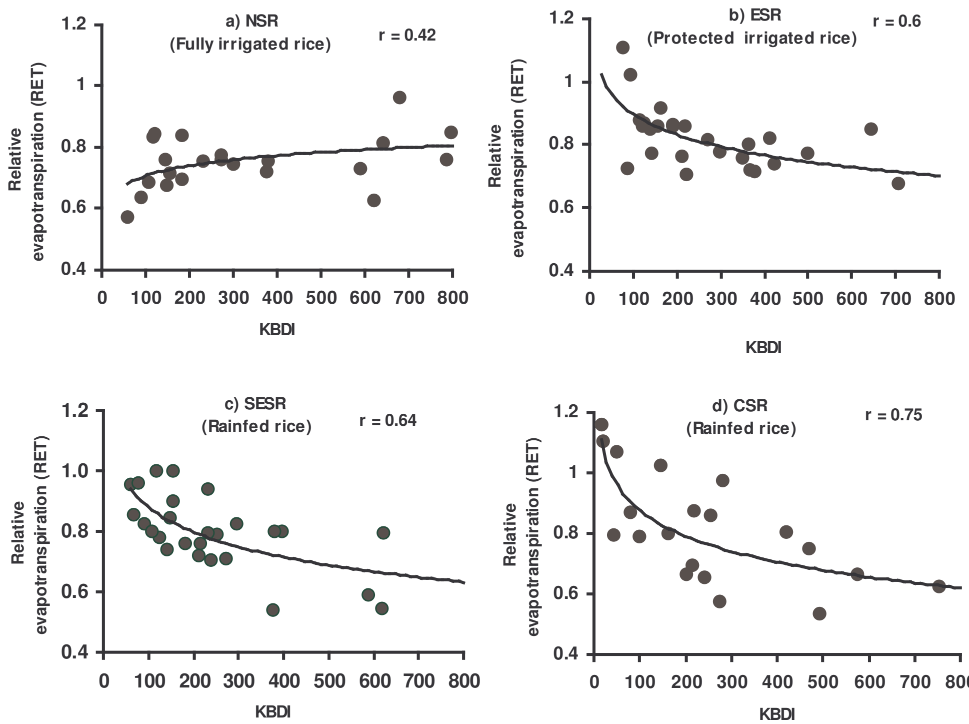

Figure 2: Relative evapotranspiration versus Keetch-Byram Drought Index (KBDI) in different rice growing conditions

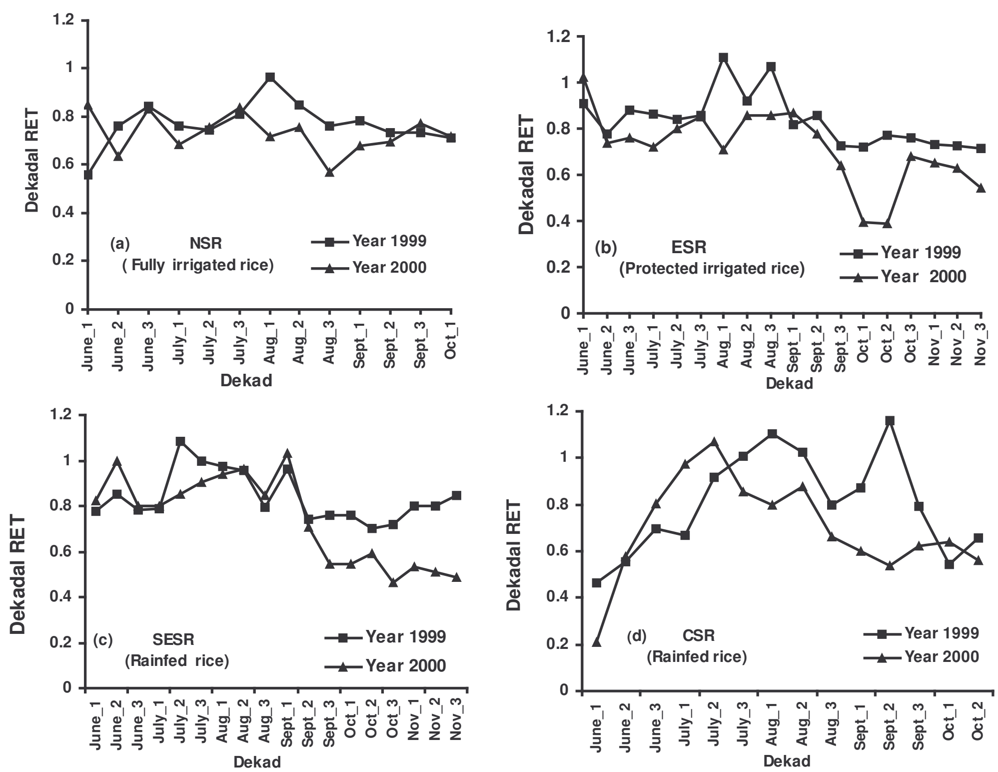

Figure 3. Seasonal variation of relative evapotranspiration in two contrasting years over four different rice growing conditions

The dekads corresponding to spectral emergence (t_o) and physiological maturity (t_{end}) representative for a district, were determined from temporal profile of rice fractional vegetation cover averaged over each district. District wise crop growing period (G) was computed as '$t_{end} – t_o$' in dekads. Fractional vegetation cover was computed from NDVI as {(NDVI – $NDVI_{min}$) / ($NDVI_{max}$ – $NDVI_{min}$)}^2 given by Carlson and Ripley (1997). The upper ($NDVI_{max}$) and lower NDVI ($NDVI_{min}$) limits were kept at 0.75 and 0.10, respectively.
District wise crop response factor (Ky) was computed for crop growth cycle (t = G) as well as for G –1(one dekad less), G – 2(two dekads less), G –3(three dekads less), G – 4(four dekads less) and G – 5(five dekads less) periods from rice RET and Ry of three intermediate years, 1997, 1998 and 1999. The average Ky for different periods within growth cycle was computed by averaging from all districts and three years. These (Table 2)

Period for prediction	Common crop response factor (Ky)	Correlation (percent)	RMSE (Kg ha^{-1})	RMSE (% of observed mean)
G	1.1	85.4	286	35.7
G-1	1.2	74.8	353	44.2
G-2	0.9	86.0	275	34.4
G-3	1.3	84.5	292	36.5
G-4	1.4	85.3	278	34.8
G-5	1.3	77.8	379	47.5

G = Whole growing period, G-1 = one dekad less than G, G-2 = two dekads less than G, G-3 = three dekads less than G, G-4= four dekads less than G, G-5= five dekads less than G

Table 2: Summary of crop response factors, correlation and errors of yield prediction in Madhya Pradesh state in India.

varied from 0.9 to 1.4. Kassam and Smith (2001) have reported 1.1 and 1.05 crop response factors for Alfafalfa grass and spring wheat, respectively. The reported district yield representing potential yield (Ry = 1) of corresponding district and falling within these three years was not considered for Ky computation.
Finally, the Ky and potential yield were used to predict rice yield using RET determined as a ratio of AET and PET accumulated for G, G -1, G-2, G-3, G-4 and G-5. Here, the predictive seasons were Kharif 1996 and 2000. The root mean square error (RMSE) of predicted yield at district level varied from 275 to 379 $Kgha^{-1}$ that constitute 34.4 to 47.5 percent of observed mean with least occurring at G –2 and highest at G – 5. These two generally correspond grain filling and booting stages of rice crop, respectively. The correlation (r) between predicted and reported yield varied from 74.8 to 86.0 percent with highest in G-2. The 1:1 plot of predicted (when RET was computed for whole crop growth cycle) and observed district rice yield of Madhya Pradesh state for Kharif 1996 and 2000, is shown in Figure 4.

The district level yield prediction using RET from coarser resolution NOAA PAL composited datasets showed relatively larger errors (mean RMSE ~ 38 percent). The possible sources of errors are enumerated below:

(a) Only clear sky RET from dakadal composites were used for yield prediction. The process of compositing takes maximum values from ten daily datasets to minimize cloud interference. This smoothes out the actual daily RET. The sensitivity analysis (not presented here) showed the transmissivity is the most crucial parameter for RET estimation followed by air temperature, LST and NDVI. Generally, substantial reduction of transmissivity occurs in cloudy skies to the tune of 0.3 – 0.5 that reduce RET in the range of 30-40 percent. RET generated on daily scale for both clear and cloudy sky conditions need to be used for better representativeness. So, use of insolation in clear and cloudy skies as well as clear sky LST, albedo and NDVI from geostationary satellite would be ideal.
(b) Present algorithm generates ET at noon time that was converted to daily scale. ET averaging on daily scale from diurnal observations contribute less errors. The diurnal observations can only be met from geostationary sensors.
(c)There is significant orbital drift in NOAA AVHRR observations from 13:30 to 15:30 hrs. IST for the same location between 1996 to 2000. These might have added less errors to angular normalized reflectances and NDVI, but could contribute errors in LST from single noon time observations. It is better to use same noon time observations from same platform.
(d) RET was generated at coarser (8km) spatial resolution and then district average of RET was made from pixels dominated by rice crop. The weightage of RET of rice area occupying less than 64 sq. km area is not included in district averaging. This could add to RET errors for rice yield prediction.

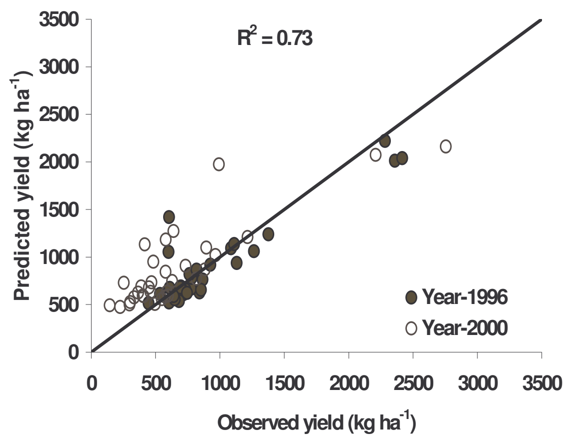

Figure 4. Comparison of district wise predicted and observed rice yield

(e)The maximum historical reported district yield was used as surrogate for potential yield. This is not always true which could add more errors to actual yield estimates from relative yield. Crop simulation model can be used to estimate district potential yield using climatology of weather parameters.

5. CONCLUSION

The present study demonstrates the use of relative evapotranspiration as growing environment indicator in rice agro-ecosystem and its further use for yield prediction in rainfed system. RET was able to differentiate a normal and sub-normal monsoon years. It has inverse correlation with meteorological drought index (KBDI) only in the rainfed agriculture but has no correlation in irrigated agriculture, which is not dependent on rainfall.

The accuracy of yield prediction using coarser resolution RET was evaluated at district level and five different time duration within the crop growth cycle between 50 days before maturity to end of growing season. The overall mean RMS error was within 38 percent of observed mean using two years validation datasets. The enumeration of possible sources of errors suggest that the diurnal observations from relatively finer resolution satellite sensors and use of crop simulation model may be ideal to reduce errors in yield prediction.

The present INSAT 3A mission has VHRR and CCD sensors. VHRR has broad optical band at 2km apart from water vapour and single thermal band at 8km spatial resolution. The daily NDVI at 1km is derivable from CCD Data. The future INSAT 3D will have six band 'Imager' with optical (1km) and split thermal (4km) bands, and 19 channel 'Sounder' (10km). The retrieval accuracy of LST, albedo and insolation from 'Imager' would be better than VHRR. The near surface air and dew point temperatures are derivable from their atmospheric profiles using sounder data. So, the use of the RET estimation technique within the framework of energy balance approach is feasible on daily scale both for clear and cloudy skies with multiple observations from India's present (3A CCD) and future (3D Imager and Sounder) geostationary sensors.

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