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Large scale soil moisture estimation using microwave radiometer data

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ABSTRACT

NIMBUS-SMMR data of 1984 and 1987 have been used to develop an algorithm for the estimation of large area soil moisture over the Indian region. Microwave brightness temperatures at 6 and 10 GHz have been empirically related to Antecedent Precipitation Index (API). Data from IRS P4-MSMR with similar frequencies will be used to estimate soil moisture with a reasonable accuracy. These estimates at scales comparable to climate model grid size would be used as initial boundary conditions in the simulation of monsoon rainfall in the Extended Range Monsoon Prediction.

Key words : Microwave radiometer, Soil moisture estimation, NIMBUS-SMMR, IRS P4 - MSMR

Surface soil moisture is perhaps the most important indicator of land surface response to atmospheric forcing and provides feedback to the atmosphere. The study of global climate using GCMs has shown that soil moisture is a very important factor (Rowntree and Bolton, 1983, Mintz 1984). From the point of view of large scale modeling, it is important to have observation values (of soil moisture) on scales comparable to modeling scales. Remotely sensed data are useful in this regard and also important for the purposes of understanding spatial variability and regional scales and in verifying land surface parameterization (Wood, 1991).

The presently available passive microwave radiometers are not optimal for 'land sensing' in terms of frequency and spatial resolution, particularly for soil moisture sensing. The Scanning Multi-channel Microwave Radiometer (SMMR) on board Nimbus -7 had a spatial resolution of approximately 150 km at 6.6 GHz. The large heterogeneity that would be present in such a large foot-print makes the interpretation very difficult. The SSM/I onboard DMSP has a lowest frequency of 19.3 Ghz, at which vegetation cover dominates the soil moisture signal. In general, frequencies below 3 GHz (e.g. 1.4 GHz) are preferred for soil moisture sensing since the attenuation through vegetation is less. However, under moderate vegetation conditions the 6.6 and 10.7 GHz channels have adequate sensitivity to surface soil moisture.

The P4-MSMR (Multi-channel Scanning Microwave Radiometer), launched in May 1999, has 6.6 and 10.65 GHz channels, in addition to 18 and 21 GHz channels. In addition to atmospheric and oceanic parameters, a few land related parameters like surface soil moisture can be retrieved with reasonable accuracy. We have carried out preliminary feasibility study using Nimbus-SMMR data (with similar frequencies) for the estimation of soil moisture over Indian region.

Njoku and Li (1999) have simulated the brightness temperatures at SMMR frequencies using Radiative Transfer (RT) model, which clearly shows that the sensitivity of brightness temperature to moisture and vegetation is greater at H than V polarization. The different sensitivity of brightness temperature to soil moisture and vegetation water content as a function of frequency and polarization allows the retrieval of soil moisture using a multi-channel algorithm. Vinnikov *et al.* (1999) examined Nimbus-7 SMMR midnight microwave brightness temperatures on a 0.5° x 0.5° grid and compared them with direct soil moisture measurements at 14 sites in Illinois (US) for the period 1982-1987. The results suggested that both the polarisation difference and the microwave emissivity for horizontal polarization at frequencies ≤ 18 GHz have real utility for use as a soil moisture information source in regions with grass or crops where the vegetation is not too dense.

The IRS-P4 Satellite carries a Multi-channel Scanning Microwave Radiometer (MSMR) operating at 6.6, 10.65, 18 and 21 GHz with spatial resolutions varying between 150 and 40 km. The data at these frequencies (with horizontal and vertical polariazations) are expected to provide a number of geophysical parameters including sea surface temperature, liquid water content, total water vapor content and sea surface winds. In addition MSMR data would also be useful in providing estimates of large area soil moisture and rainfall rates.

To facilitate the development of an algorithm for the estimation of soil moisture, a limited data set of NIMBUS-7 SMMR during May 15 - July 20 for the years 1984 (Good Monsoon year) and 1987 (Drought year) were procured. The meteorological data like weekly rainfall, average maximum and minimum temperature over the various subdivisions as provided by India Meteorology Department were collected for the computation of Antecedent Precipitation Index (API). This index is taken as representative of soil moisture and is computed under the assumption that rainfall is the major forcing variable for soil wetness.

MATERIALS AND METHODS

Antecedent precipitation index (API)

Weekly variations of soil moisture over different subdivisions over India are calculated using the API model developed by Choudhury and Blanchard (1983). The model is physically based, and has been shown to predict realistically the temporal changes in soil moisture. We are assuming its validity over our study area (India).

The maximum depth of soil water available for evaporation (W_m) is a complex function of soil texture, compaction and plant rooting depth (which varies with age, species and its water stress conditions). We lack detailed information needed to quantify its spatial and temporal variability. We assumed a rooting depth of 100 mm, giving $W_m = 30$ mm. The weekly average API was then determined for each sub-division. The maximum water holding capacity of the soil was taken to be 25 mm, based on the results of a sensitivity analysis given in Choudhury *et al.* (1987). The 25 mm water capacity represents a surface profile of 4 to 6 cm depth.

Linear regression between SMMR 6.6 GHz brightness tempreture (Tb) and API was performed for 15 northern quadrants (of the study area over US Great plains, Choudhary *et al.* 1987) with API as the independent variable

$$Tb = a + b * API$$

Tb was found well correlated with API. API accounted for more than 70 percent of the temporal variability in Tb (i.e., $R^2 > 0.70$ for 10 out of 15 quadrants). The slope (b) of the regression equation was found to be steepest for the least vegetated quadrants and decreased as vegetation became denser. These slopes (b) and intercepts (a) were regressed with NDVI and found to be well correlated (r = .92) for slope 'b' vs NDVI; and r = .50 for intercept 'a' vs NDVI). The final regression equation with the vegetation effect is

$$API_c = \frac{(269 + 32.6 * NDVI - Tb6H)}{(7.35 - 13.7 * NDVI)} \quad \ldots (1)$$

Regression equation for the pooled data set for all quadrants when vegetation effect was not considered is :

$$API_c = 105.4 - 0.38 * Tb6H \quad \ldots (2)$$

These empirical relations gave very good estimate of soil moisture information over US Great Plains with the r.m.s. error of 1.9 mm using Tb and NDVI both (equation-1) and 2.8 mm without including vegetation effect (equation-2).

These empirical relations (2) when applied to Indian region did not give correct estimates of soil moisture conditions (r.m.s. error of ~9.5 mm) when compared with the API. Therefore, it is necessary to determine new empirical relation for Indian regions. In the following sections we describe the development of new empirical relation between brightness temperature and API.

RESULTS AND DISCUSSION

The coefficients developed over the US plains are expected to be quite different over the Indian region, in view of large differences between soil types, soil texture, surface roughness, agricultural practices adopted. The basic approach of establishing empirical relationship between API and Tb for Indian region remains same as that of Bhaskar Chaudhury, as discussed above. However, in absence of daily data for rainfall and average surface temperature at hand, we used weekly data (Weekly Weather Report, 1984 and 1987) for 35 subdivisions over India. For this study

Table 1 : Empirical relationships obtained for the Indian region between Nimbus - SMMR channels Tb and API for the year 1987.

Channel	Empirical relation Tb vs API	Coeff. of Correlation, r
6H	Tb6H = -1.943 API + 261.4	0.77
6V	Tb6V = -1.609 API + 283.1	0.75
10H	Tb10H = -1.684 API + 268.9	0.75
10V	Tb10V = -1.407 API + 286.3	0.74
18H	Tb18H = -1.361 API + 272.8	0.68
18V	Tb18V = -1.206 API + 286.1	0.66

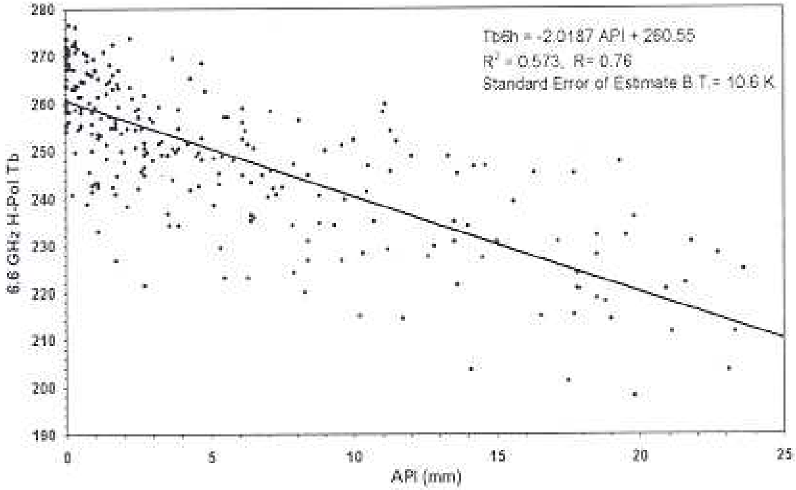


Fig. 1 : API vs 6.6 GHz H-Pol brightness temperature (Nimbus-SMMR 1984 & 87)

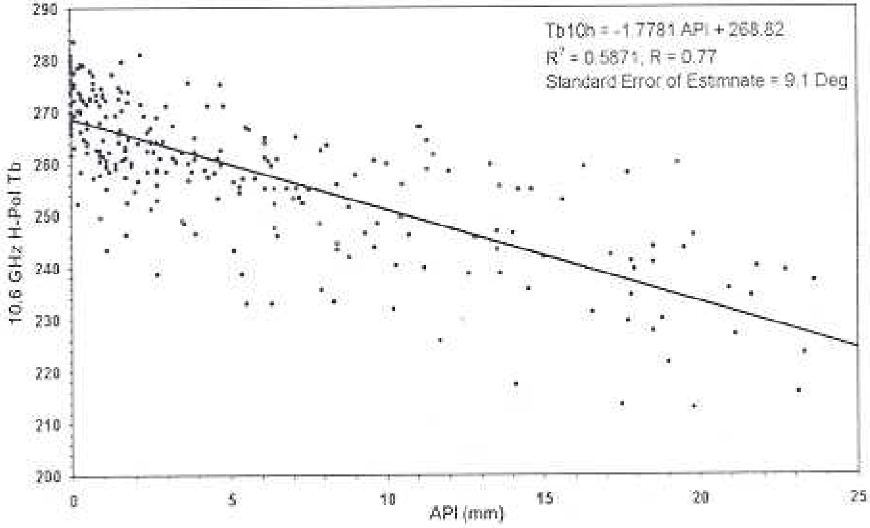


Fig. 2 : API vs 10.6 GHz H-Pol brightness temperature (Nimbus-SMMR 1984 & 87)

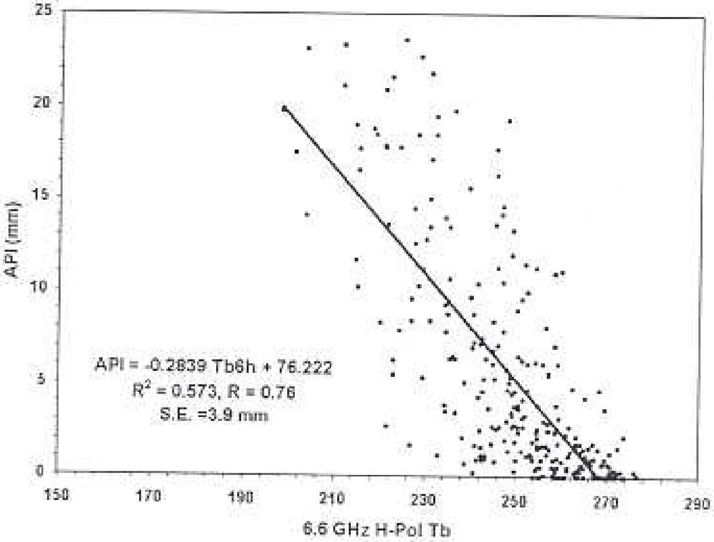


Fig. 3 : SMMR 6.6 GHz H-Pol Tb vs API (1984 & 87)

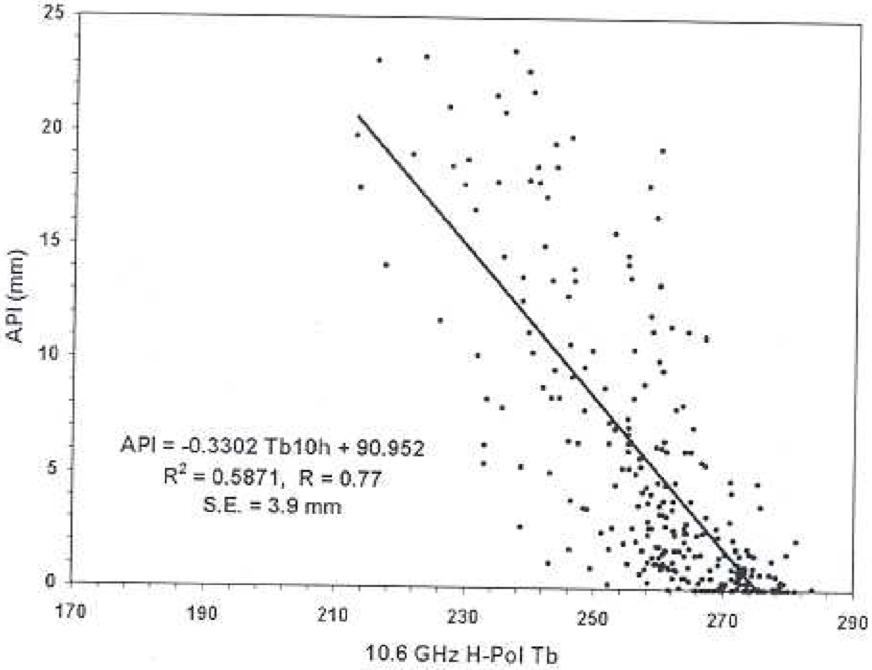
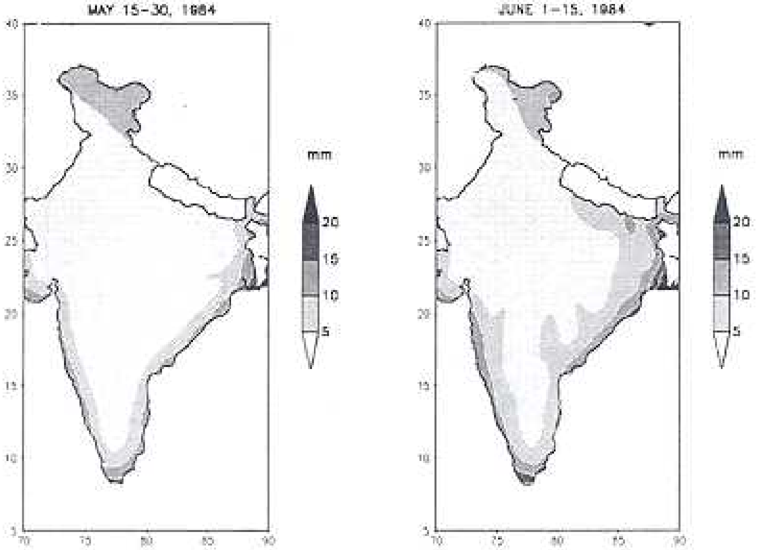


Fig. 4 : SMMR 10.6 GHz H-Pol Tb vs API (1984 & 87)


MAY 15-30, 1984

JUNE 1-15, 1984

Fig. 5 : Estimated API using SMMR 6.6 GHz H-Pol

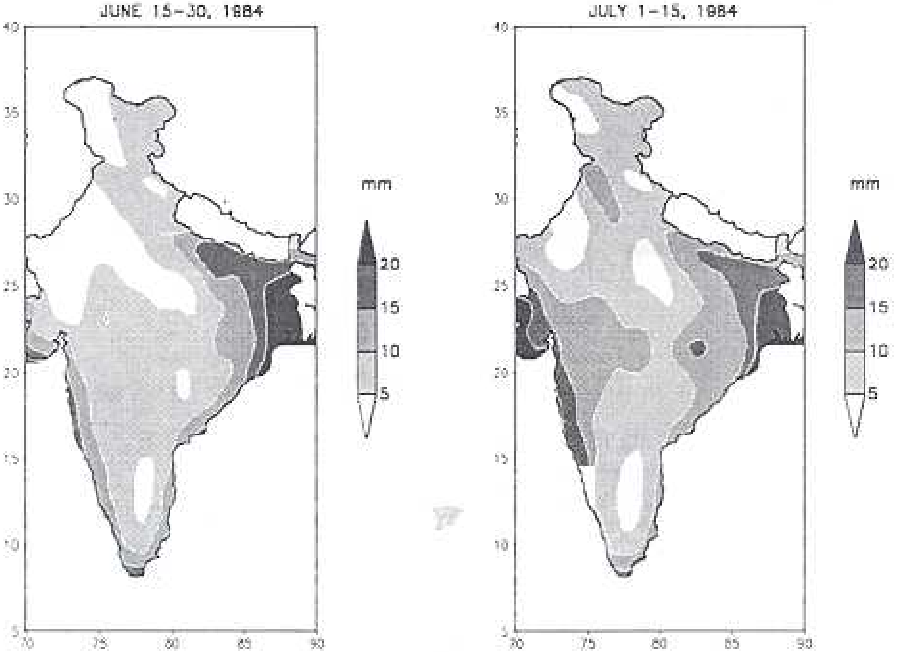

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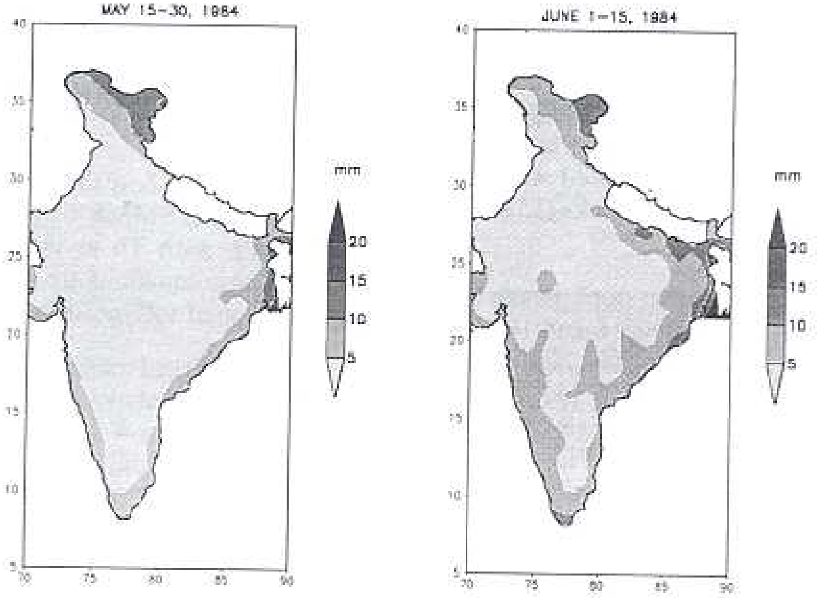
Fig. 6 : Estimated API using SMMR 6.6 GHz H-Pol



MAY 15-30, 1984

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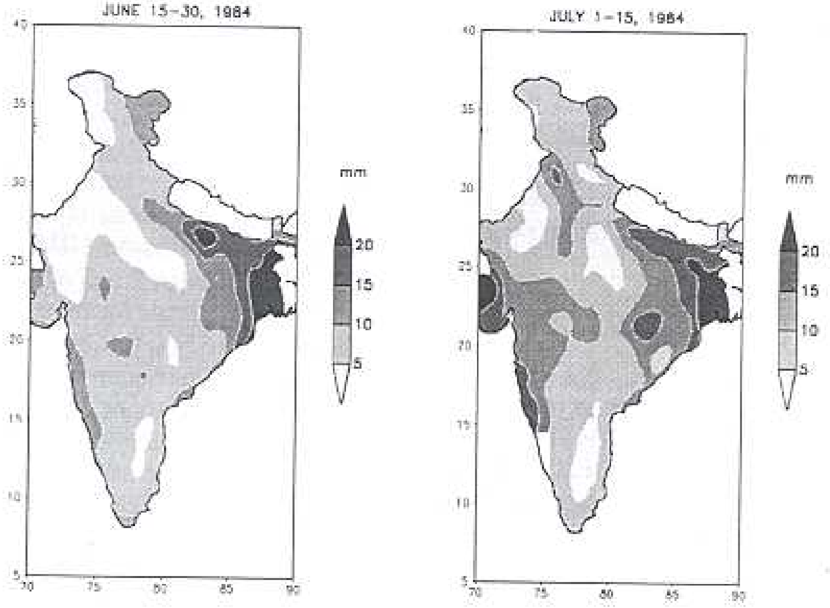
Fig. 7 : Estimated API using SMMR 10.6 GHz H-Pol



JUNE 15-30, 1984

JULY 1-15, 1984

Fig. 8 : Estimated API using SMMR 10.6 GHz H-Pol

we have excluded the subdivisions with high mountains and deep forests and also those subdivisions, which are very close to ocean. Weekly average SMMR- brightness temperatures for different channels over these subdivisions are then regressed with the weekly calculated API for 8 weeks (15 May - 15 July).

It is seen (Table 1) that slope parameters for the relationship involving 6 and 10 GHz (H polarisation) is maximum with high degree of correlation (>0.75). While 6 and 10 GHz (V polarisation) also show a high degree of correlation between Tb and API, the slope values are relatively less as compared to horizontal polarisation. For 18GHz (H and V), both slope as well as the correlation coefficient is considerably small, thus showing a poor relationship. Similar results were obtained for the year 1984.

The pooled data set of Nimbus-SMMR of 1984 and 1987 showed consistent results. Based on the above conclusions, we have analysed the 6 and 10 GHZ (H pol.) for deriving working relationships for the estimation of soil moisture over India. Regression of 6.6 GHz (H) Tb with API (Fig.1) shows very good correlation (r = 0.76). The equation is :

$$Tb6H = -2.02 * API + 260.55 \quad \dots (3)$$

The r.m.s error in soil moisture estimation from this equation is found to be 3.9 mm. Thus it can be used to give three broad categories of soil moisture conditions. This estimate can be improved by including vegetation effect into the regression equation.

A similar relation for 10.7 GHz (H) and API is given by

$$Tb10H = -1.78 * API + 268.82 \quad \dots (7)$$

with r = 0.77 (Fig.2). The r.m.s error in soil moisture estimation from this equation is found to be 3.9 mm.

Figs. 3 and 4 show the linear regression analysis between SMMR 6 and 10 GHz (H) Tb and API, with Tb as the independent variable. These equations are further used for the generation of soil moisture maps.

Using empirical relationship between Tb and API as derived above, we have calculated the soil moisture for 4 fortnights viz. 16-31 May (May-I), 1-15 June (Jun-I), 16-30 Jun (Jun-II) and 1-15 July (Jul-I) for 1984 (Fig.5 to 8). These maps of different phases of 1984 monsoon season bring out the important features of the soil moisture variations over the Indian region during May-July. The gradual increase of soil moisture from June to July and over the Gangetic plains and the peninsula are clearly seen. Soil moisture estimated from SMMR data for the above 4 periods compare very well with the API maps (not shown). This analysis clearly shows the sensitivity of SMMR data at 6 and 10 GHz (at H polarisation) to soil moisture variations. The encouraging results obtained in this feasibility study using NIMBUS - SMMR data for the estimation of large area soil moisture is the basis for the utilisation of P4-MSMR data. For the empirical equation establishment daily rainfall and temperature data over Indian stations is required in addition of daily Tb's. NDVI over the different regions will be incorporated using regression of slope (b) vs NDVI and intercept (a) vs NDVI. This will give more accurate determination of soil moisture over Indian region, accounting for the effect of the vegetation. These more refined relationships can then be used for soil moisture estimation using MSMR data.

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