ESTIMATING WHEAT YIELD: AN APPROACH FOR ESTIMATING NUMBER OF GRAINS USING CROSS-POLARISED ENVISAT-1 ASAR DATA

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ABSTRACT

In this paper an attempt to model wheat yield is made by exploiting characteristic interaction of cross-polarised SAR with wheat crop. SAR backscatter from a crop field is affected by the density, structure, volume and the moisture content of various components of plant (viz. head, stem, leaf) alongwith soil moisture. Hence, to effectively handle the influence of each of these components of the plant on SAR backscatter, a plant parameter, termed as Interaction Factor (IF) is conceptualised by combining volume, moisture, height for each of the component and density of plant. For this purpose, detailed experiment over farmers' fields was carried out in synchrony with SAR acquisition involving in-depth measurements on volume, moisture content and height of various components of wheat plant, number of grains, plant density and soil moisture. Stepwise regression analysis revealed that IF_{Head} significantly affects the shallow incidence angle, cross-polarised C-band SAR backscatter. IF_{Head} is also highly correlated to the number of grains. This is attributed to the fact that parameters of the wheat head from which IF_{Head} is calculated, namely moisture, volume and height, determine eventual number of grains. The study offers an approach for estimating wheat yield by retrieving number of grains from shallow incidence angle cross-polarised SAR data.

Keywords: Envisat-1 ASAR, SAR Backscatter, wheat yield, number of grains, head, leaf, stem, crop volume, crop biomass, crop moisture, soil moisture.

1. INTRODUCTION

Modelling yield of a crop is a challenging area of research for many researchers. Many approaches like biometric, econometric, weather indices, crop-weather and optical spectral models have been adopted to estimate crop yield. In addition to issues related to predictability, the scarcity of required database limits the use of most of these approaches. Optical spectral models involving single/multi-temporal optical remote sensing have also been widely used alone or in combination with other approaches like crop-weather. However, it is difficult to operationally use the approach owing to the lack of long time-series of uniform spectral data. The basis of estimating wheat yield using optical remote sensing is the impact of crop vigour on spectral signatures in optical region of electromagnetic spectrum which is governed by the micro level interaction that takes place between a standing crop and sun radiation. The effect of atmosphere and soil background often results in low correlation of yield with canopy vigour. It is the basic difference in the sensitivity of optical and synthetic aperture radar (SAR) to the different component of a crop that makes SAR a promising tool for modelling crop yield. The first and foremost is the all weather capability of SAR along with its unique sensitivity towards structure, density and moisture content of a crop canopy, which gives SAR an edge over optical remote sensing.

Modelling SAR backscatter from a vegetated area has been an active area of research [1]-[2]. A number of crop parameters have been used to describe crop plant like crop height, wet biomass, dry biomass, plant density etc. It is well known that SAR is sensitive towards structure, density and moisture content of a crop plant [3]. Its sensitivity to the different components of a crop makes SAR a promising tool for characterising a crop plant. Several studies have been carried out to understand the effect of crop growth on temporal SAR backscatter [4]-[5].

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SAR backscatter has been successfully used for crop classification [6]–[9]. The Michigan Microwave Canopy Scattering (MIMICS) model is one of the most successful models to predict SAR backscatter of forested land [10]. MIMICS has also been found to be useful even when adapted for agricultural applications like retrieval of crop biomass [11]. However, it is required to have a large number of parameters for adapting to MIMICS. Researchers have also attempted retrieval of various crop parameters using empirical as well as semi-empirical models like water cloud model. The approach is to model SAR backscatter using plant descriptor parameter and then to invert the SAR backscatter model to retrieve the plant descriptor parameter used. The crop parameters of interest have mostly been that of retrieval of crop height [12] and crop biomass [13]. Use of Leaf Area Index (LAI) has also been done as the substitute of plant descriptor to characterise SAR backscatter from crop covered fields [14]-[16]. Semi-empirical model developed by [17] has shown a good correlation with vegetation water mass at L-band VV polarisation. A study carried out by [18] using C and X bands confirmed that plant water content can be retrieved using Radar data. However, taking only any one of the parameter of a crop is not sufficient to characterise the crop fully as SAR is sensitive to the structure and density of a crop as well as the crop moisture and moisture content of the underneath soil. Besides, the structure of the crop in terms of the volume fraction and distribution of various components of a crop plant, like its head, leave, stem along with the moisture content of each of these component also significantly affects the radar backscatter. [19] have experimentally confirmed the effect of structure on SAR backscatter at X-band using ground based radar. It is felt that any single parameter is not sufficient to fully characterize the SAR interaction to crop. Therefore in this study, component wise volume, moisture, height and density has been combined to arrive at a plant parameter, which can better characterize the SAR interaction to different layers of wheat crop. The sensor parameters also play a significant role in the SAR sensitivity to crop plant because it is the sensor parameters like frequency, polarisation and angle of incidence that determines the dominance of the different component on to radar return signal. SAR backscatter from longer wavelength is influenced by most of the components of the crop along with that of underneath soil as longer wavelength penetrates deeper in the crop. However, shorter wavelength interacts mostly with the upper crop layer hence is likely to be less influenced by the underneath soil. Similarly, shallow angle of incidence is likely to intercept more of the crop as compared to steep angle of incidence due to higher path length within crop. The polarization of transmit and receive SAR signal also play an important role in the impact of various components of crop on to SAR backscatter. Experiment on wheat crop under controlled laboratory environment using a ground based SAR [20] indicated that most of the signal strength at C band cross-polarised data is observed to be from upper layer of a crop canopy. Thus, cross polarised SAR backscatter at shallow angle of incidence is expected to be mostly influenced by the upper layer, namely head of the wheat crop. In this study cross polarised ENVISAT-1 ASAR data has been explored for modelling wheat yield in terms of number of grains which forms the head. The experiment for this purpose has been carried out over farmer's fields. This paper describes the experimental setup, the proposed plant parameter, developed SAR backscatter model along with its validation, inversion of the SAR backscatter model to retrieve the proposed plant parameter and finally the model relating the retrieved plant parameter to the number of grains used to reach to wheat yield and validation of the same.

2. DATASET AND STUDY AREA

For the present study, cross polarized (VH) ENVISAT-1 ASAR IS4 data, dated 11th March 2005 and 04th March 2006, at 36^{o} (central) incidence angle has been acquired over parts of Saharanpur and Haridwar districts of India. ENVISAT-1 operates at C-band (λ = 5.6 cm) with like as well as cross polarization mode along with varying incidence angles with nominal resolution of 30 meters for standard beam mode. Geographic Coordinates of the study area are 77° 28' 36"E to 77° 57' 03"E and 29° 45' 01"N to 30 ° 05' 11"N. The study area is dominated by agriculture land and major portion of the study area is covered by the alluvial, well-drained loamy soils (both coarse & fine). Two major canals are passing from this region, one is Gang canal flowing from Northeast direction to Southeast direction and another is Yamuna canal flowing from Northwest to West direction. The major crops during the time of study were wheat and sugarcane. Besides satellite SAR data, 1:50,000 scale SOI (Survey of India) toposheets were used along with a GPS based mobile mapping System.

3. EXPERIMENTAL SETUP

This investigation involves conceptualisation and development of a plant parameter which describes SAR interaction to crop plant. Execution of such an investigation demands a very sound experimental plan to collect ground truth observation from sampling fields in synchrony with Envisat–1 ASAR passes. Since the experiment is conducted in farmers' field, an important step here is to determine the optimum size of sampling field i.e. to arrive at the minimum required size of a farmer's field such that the backscattering coefficient derived from the field actually represents the true average backscatter of the field. This ensures developing a true relationship between backscattering coefficient and observed values of parameters from the farmers' fields. The minimum size of sampling fields was determined using Statistical approach.

3.1 Statistical Approach to Arrive at the Size of Sampling Field

In case of SAR image, the problem of fading needs to be considered to determine the minimum size of the sampling unit (i.e. minimum size of the farmers' fields appropriate for carrying out the sampling). Fading is a phenomenon in radar system, due to which the random fluctuations of the return signal, observed from an area extensive target, produces speckles on the image. Therefore good estimates of the backscattering coefficients are obtained only if enough pixels are averaged over an area extended target like farmer's field [21]. The number of pixels required to be averaged determines the size of the sampling unit, i.e. the field.

If a resolution cell value is the amplitude of random return signal, the probability distribution function is described by Rayleigh distribution for the single look image [22].

$$P(x) = \frac{\pi x}{2\mu^2} \exp\left[\frac{-\pi}{4\mu^2} x^2\right], \qquad 0 < x < \infty \tag{1}$$

where P(x) is the probability of a resolution cell to have an amplitude between x and x + d x, μ is the mean value of x. The variance σ^2 is given by

$$\sigma^2 = \int_0^\infty P(x)(x-\mu)^2 dx \tag{2}$$

The number of resolution cells, N, required for an estimate of the average amplitude with a given error at a given confidence interval can be determined by the probability approach of arriving at an estimate of the μ as follows:

$$P(|\bar{x} - \mu| < \Delta\mu) = 1 - \alpha \tag{3}$$

Where, α is the level of significance and

$\Delta\mu$ is the margin of permissible error

$\bar{x}$ is the average of the N samples observation.

By following the procedures as described by Patel, et. al., [23] we get the required sample size for an error of 10% on the signal amplitude i.e. $\alpha = 0.1$, and at 90% confidence interval ($Z_{\alpha/2} = Z_{.05} = 1.64$) as

$$N = (1.64 * 0.523/0.1)^2 \tag{4}$$

Thus we get N = 74 for an error of 10% on the signal amplitude and at 90% confidence interval. Hence, 74 pixels should be averaged to get an estimate of backscattering co-efficient with an error of 10% on the signal amplitude and 90% confidence.

For the case of 3 look, ENVISAT-1 ASAR data with nominal resolution of 30 meters, we get 74*30*30 = 66600 m^2 area as the required size of sampling unit. Since multi-looking reduces the required size of samples to arrive at an estimate to backscattering coefficient by the number of looks, the minimum area to be taken as the size of the sampling unit is computed as $66600 m^2/3 = 22200 m^2 = 148.99 \times 148.99 m^2 \sim 150 \times 150 m^2$ to get an average signal amplitude with an error of 10 % at 90% confidence interval. Thus the required size of sampling field corresponds to 5x5 resolution cells on the Envisat-1 ASAR image.

3.2 Measurements of Plant and Soil Parameters

Identification of the sampling locations on SAR images has always been a challenging task particularly when only a single channel SAR data is used. Whenever experiment is conducted over farmers' fields, most of the time sampling fields have to be chosen in such a way that they have to fall near ground control points (GCPs) like rail/road/canal crossings. However it is not always feasible to identify the rail and road network unless the look direction and the direction of rail/road lines are orthogonal to each other. If the road/rail lines are parallel to the look direction then it is difficult to detect them. Hence even when the sampling fields are chosen to fall at GCP's like rail/road or road/road crossings, it is still not guaranteed that it will certainly be identified on the image. Moreover, if they are not near the sampling field then identification of sampling fields are extremely difficult. Therefore even with some amount of uncertainty, it becomes a compulsion to always select sampling fields near a ground control point. This in turn restricts the kind of variability in the characteristics of the sampling field that is required to carry out a specific study in farmers' fields. Moreover the stringent requirement of farmers' field size being larger than 150x150 m^2 also adds to the restrictions. For example, one may not be able to locate enough number of large wheat fields near GCP's which is required to carry out this particular study. Particularly in India, the field size is often very small. It could even be less than 100m x 100m. To overcome these difficulties the authors have come up with a practical solution that of using a Global Positioning System (GPS) based mobile mapping unit to trace the boundaries of each of the farmers' sampling field as shown in figure-1. Along with the field boundary, the road network that is being en-routed to collect the samples from farmer's fields is also being mapped. The mobile mapping unit provides the vector layers in UTM projections with detailed information of each of the sampling field as output layer. Later on while carrying out image processing these vector layers are superimposed on the geo-referenced SAR images. Adopting this procedure not only ensured the identification of the farmer's fields on SAR image with high accuracy, but also removed the restriction of selection of the sampling field at or near the GCP's. At the same time it also ensured accurate assessment of the field size.

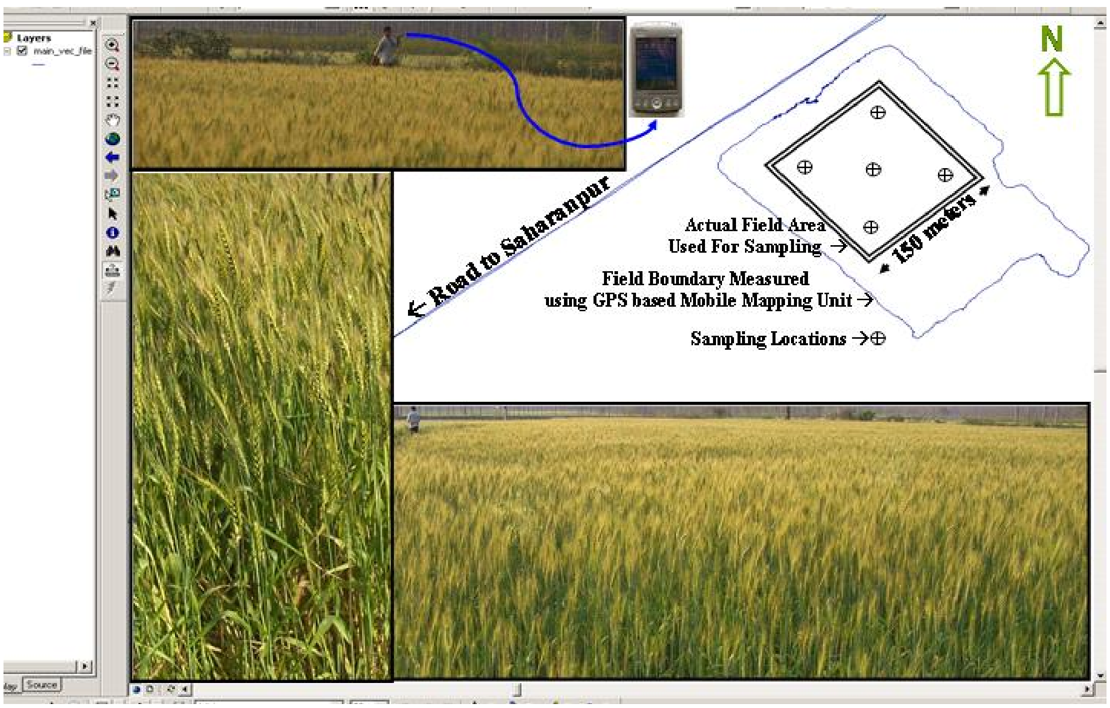

Fig. 1. A typical example of the sampling field boundary as traced using GPS based mobile mapping unit. The sampling location within the sampling field are also shown.

By adopting the above described approach, the experiment has been conducted on framer's fields that were larger than 150x150 m^2. The data was collected during the month of March 2005 and March 2006 in synchrony with Envisat-1 ASAR passes. Detailed field parameter collection was planned in order to fully characterise the backscattering response from the wheat crop. In order to fully characterise interaction of SAR to wheat crop, the crop was segmented in to three components namely, stem, leave and the head of the wheat plant. The parameters measured are volume, moisture and height/length of all the three individual components (head, leave and stem), moisture of the underlying soil alongwith percentage cover and plant density. For the purpose of measurement of volume and moisture of different component of the plant, twenty five plants from each of the sampling field were selected as depicted in figure-1. All the three components (head, leave and stem) of wheat plant were separated from each other by cutting each of the wheat plant.

Number of wheat grains were counted from the wheat heads. The fresh weights of all the three components were separately measured. Then volume of each of the components was separately measured using glass measuring cylinders as shown in figure-2.

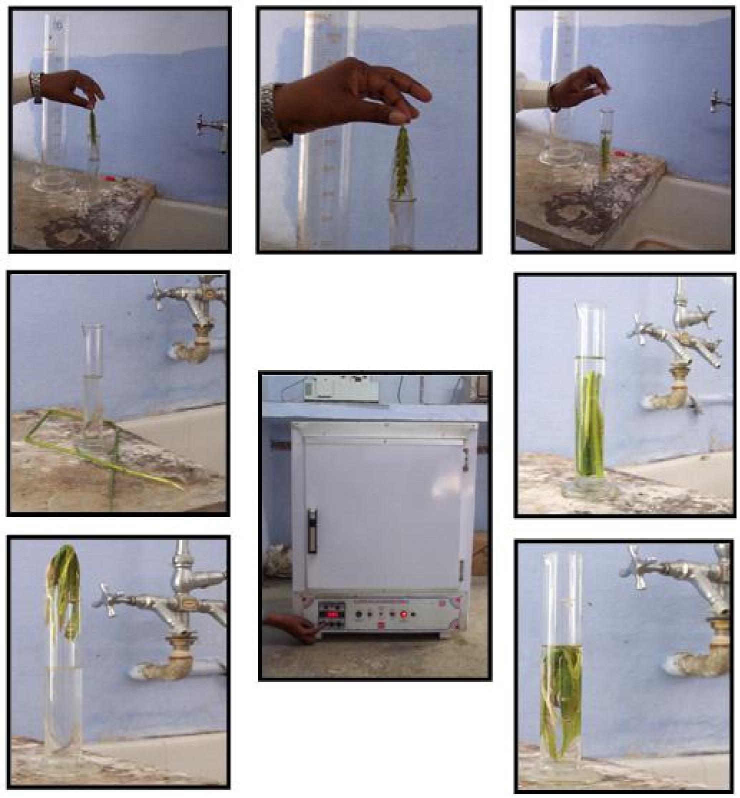

Fig. 2.. Measuring volume of different component of wheat crop

Following the volume measurement, all these components were then oven dried at 85^{o} C temperature for 24 hours in an electrical oven fitted with digital temperature controller. Once oven dried, the dry weight of these components was measured to arrive at dry biomass. The dry and wet biomass was used to arrive at moisture content of individual plant component. Volumetric soil samples at 0-5cm depth were collected from the soil underneath the wheat crop using a tube auger. Fresh weight of the soil samples was noted and the samples were oven dried at 105^{o} C temperature for 24 hours. After oven drying of fresh soil samples, dry weights of the soil samples were noted and volumetric soil moisture was arrived using the fresh and dry weights of the soil samples and their respective bulk densities. The bulk density of each of the sampling locations was derived with the help of undisturbed soil sample of known volume (100 cc) with the help of a core sampler. Field parameters recorded for each of the sampling field consist of height/length of head (H_h), height/length of stem (H_s) and height/length of that portion of plant, which occupies leaf (H_l), i.e from the point where the first leaf appear to the point from where the top leaf starts dropping sideways, plant hight (H_p), plant density(N), percentage cover, wet biomass of individual component of plant (namely head, leave, stem), wet biomass of plant, dry biomass of individual component of plant (namely head, leave, stem), dry biomass of plant, ,moisture content of individual component of plant (namely M_h, M_l, M_s), moisture content of plant (M_p), volume of individual component of plant (V_h, V_l, V_s), volume of plant (V_p) and volumetric soil moisture of underneath soil. For both the years, in the month of April, the time when wheat is ready to harvest, the sampling fields were revisited and the yield observations were made.

4. INTERACTION OF RADAR SIGNAL WITH CROP PLANT

SAR signal from a crop-covered field is affected by geometry and dielectric properties of the crop. A given crop can be characterised by the size, shape and dielectric properties of its various components. The proportion of horizontally and vertically polarized components in the received backscatter is dependent on the polarization of the transmitted microwave signal and the relative orientation of the scattering elements present in the vegetation [24]. As compared to the like polarized SAR signal, cross-polarized SAR signal is likely to be more sensitive to vegetation volume owing to the depolarisation of signal that takes place during the multiple scattering of the incoming signal within the vegetation. At the same time structural properties of various components of the crop also significantly affect the cross polarised signal. The resultant backscatter is expected to be depending upon the fractional distribution of the different components of the crop having distinct structural and dielectric characteristics [25]-[26].

Thus in case of wheat crop, SAR backscatter can be considered as a composite of its interaction with head, leave and stem along with the moisture content of the underlying soil. At the same time, the distribution of the volume and moisture of each component of wheat plant determines the depth of penetration of a signal into a wheat crop. Therefore, it is neither the moisture content of each of these components nor the volume of each of these components that alone can fully describe the SAR backscatter from a wheat crop. Hence a plant parameter is conceptualised in this paper, which is combining the moisture content in a confined volume as well as the density as described in the following section.

4.1 Conceptualisation of the Crop Parameter: The Interaction Factor

As discussed in previous section, the interaction of SAR signal is not uniform over the crop plant. Different component of crop contains different moisture and the volume that each of the component occupies is also different. Thus, in order to account for the structure of crop, one needs to segment the plant in to different components. It is the moisture distribution in a given volume that affects the backscatter. Thus there is a need to have a plant parameter which is combining the volume as well as moisture of each of the component of the crop plant. The quest to arrive at a plant parameter that is able to characterise the SAR interaction to a given crop has lead to conceptualisation of a plant parameter, namely the Interaction Factor. The term Interaction Factor is coined for this plant parameter owing to the fact that it is formulated in such a way that it tries to incorporate the factors which are responsible for the interaction of SAR signal to crop which in turn determines the resultant SAR backscatter. The Interaction Factor combines the moisture content in a confined volume for each of the component for the given field. The interaction factor for the wheat crop as whole is defined as follows:

Interaction factor of whole plant (IF_{plant}) = (Plant moisture * Volume of plant * plants density) / plant height

$$= (M_p V_p N) / H_p \tag{5}$$

The Interaction factor as defined above is taking in to consideration the moisture distribution in a confined volume per unit volume for the whole plant of the wheat crop. Since the structure of a given plant also significantly affects SAR backscatter along with the volume, moisture and density, the wheat plant is segmented into three components i.e. head, leave and stem. The component wise interaction factor for each of the segment namely, the Interaction factors for head (IF_{Head}), leave (IF_{Leave}) and stem (IF_{Stem}), were calculated on the same lines as that for the whole plant as given below:

Interaction factor of head (IF_{Head}) = Moisture content of head*Volume of head * plants density/ height of head

$$= (M_h V_h N)/H_h \tag{6}$$

Interaction factor of leave (IF_{Leave}) = Moisture content of leave*Volume of leave*plant density/height of leave

$$= (M_l V_l N)/H_l \tag{7}$$

Interaction factor of leave (IF_{Stem}) = Moisture content of stem*Volume of stem*plant density/ height of stem

$$= (M_s V_s N)/H_s \tag{8}$$

5. DATA PROCESSING

5.1 DN to σ° conversion

The DN values of Envisat-1 ASAR image can vary for scene to scene, making it difficult to directly relate information between scenes. Hence for any quantitative analysis, it is necessary to convert the DN image data to calibrated radar backscatter (Sigma naught) data. For the Envisat-1 ASAR data, 'BEST' software was used to arrive at radiometricaly calibrated SAR backscatter image. First step is to convert the data to power. Once the image is converted to power, the radiometric effects for the incidence angle and absolute calibration constant were corrected.

$$\sigma^{o}{}_{VH}\, dB = 10.0 \times \log_{10}(Power) - absolute\_calibration\_Constant + 10.0 \times \log_{10}(\sin(\alpha)) \qquad (9)$$

Where DN is the digital number of SAR image, which is in Power. α is the local incidence angle at that pixel position in the range direction. The absolute calibration constant was taken from the header of Envisat-1 ASAR image. The header information was also used for calculation of α, the local incidence angle at each pixel. These conversions yielded a 32bit real image of $\sigma°$ in dB.

5.2 Image Processing

After conversion of DN to $\sigma°$, speckle suppression was carried out using Enhanced Lee-filtering algorithm [27]. 11-March-2005 image of ENVISAT-1 ASAR S4 beam mode data was geo-referenced using the Ground Control Points (GCPs) from 1:50,000 scale Survey of India (SOI) topographic map and GPS measurements at the ground control points [28]. The Envisat-1 ASAR image of 04-Mar-2006 was then geo-referenced with respect to 11-Mar-2005 image of Envisat-1 ASAR. The vector layers of rail/road/canal network, farmer's field boundaries, the actual sampling locations generated with the help of GPS based mobile mapping unit, were transferred on to the image. There after all the 46 sampling fields locations were identified on the images and their backscattering coefficient values, σ^0 were extracted from Envisat-1 ASAR images of 2005 and 2006. Out of these 46 observations, 10 were randomly selected for validation data set and the rest 36 were used to develop the model.

6. RESULTS AND DISCUSSION

In order to demonstrate the effectiveness of the concept of interaction factor, the analysis is carried out in two steps. In the first step effect of a variety of vegetation parameters measured in the field along with the effect of soil moisture underneath wheat crop on SAR backscatter at VH polarisation (σ^0_{VH}) has been examined. Next the SAR backscatter is modelled using the concept of interaction factor of individual layers which is proposed in this study. For this purpose, observations from 36 farmers' fields were used. In the second step, SAR backscatter is validated using validation dataset consisting of observations from 10 sampling fields. The following subsection describes details of the developed models at each of these steps.

6.1 Modelling Backscattering from Wheat

Once the backscatter coefficient from cross-polarized (VH) ENVISAT-1 ASAR images were extracted for all the 46 fields, the interaction factors of whole plant, head, leave and stem were arrived at using the ground observation from the corresponding wheat fields using expressions (5), (6), (7) and (8). In order to appreciate the combined effect of the three interaction factors as defined in section 4.1, firstly empirical model relating σ^0_{VH} to the $IF_{(plant)}$ and moisture content of soil underneath wheat crop was carried out using stepwise regression analysis. The soil moisture was excluded from the regression analysis with the criterion of probability of F to remove >= 0.10, and probability of F to enter <= 0.05.

The model is given by

$$\sigma^0_{VH} = A + B * IF_{(plant)} \qquad (10)$$

The R^2 value was observed to be 0.71 with value of F statistic being 83.33 (Significance of F = 1.14E-10).

Since the structure of wheat plant also plays an important role in the scattering/attenuation of incoming signal from a given crop field, in particular in our case for the wheat crop, it was felt that study of SAR backscatter in terms of component wise interaction factors would lead to more insight in to the interactions that takes place between SAR signal and different component of crop plant. Hence, an empirical model using stepwise linear regression analysis relating σ^o to the individual Interaction factors (i.e. IF_{leave} , IF_{stem} ,IF_{head}) and the moisture content of soil underneath wheat crop was performed as follows

$$\sigma^0_{VH} = A + B * \text{Soil Moisture} + C * IF_{leave} + D * IF_{stem} + E * IF_{head} \qquad (11)$$

The soil moisture, IF_{stem} and IF_{leave} were excluded from the regression analysis with the probability of F to remove >= 0.10, and the probability of F to enter <= 0.05.

Thus the model arrived at is

$$\sigma^0_{VH} = A + B * IF_{head} \qquad (12)$$

The R^2 value was observed to be 0.78 with F value being 125.86 (Significance of F = 5.66E-13) with the standard error of y estimate observed to be 0.65. The study of the regression analysis results in terms of significance of F value and the coefficient of determination for the plant interaction factor (IF_{plant}) and individual interaction factors, shows that the VH polarised C-band SAR backscatter at higher incidence angle is more sensitive to the upper component of the crop. That is σ^0_{VH} is affected most by IF_{head} as compared to the lower components of the crop (IF_{stem}, IF_{leaf}), moisture content of the soil. These findings support the soundness of the approach to segment the wheat crop and then examining the dependence of SAR backscatter on different layers.

6.2 Validation of the Vegetation Backscatter Model

Validation is an essential component of a statistical approach based analysis. It requires having a validation data set consisting of independent observations of the parameter to be estimated such that these observed values of the parameters are not used to arrive at an estimate of the parameter. Moreover the size of validation sample is equally important. In our study, the size of validation data set required have been determined using precision power approach as suggested by [29] keeping the criteria that the sample correlation coefficient is not to decrease by more than .05 no matter what the expected value of correlation coefficient is. Using this approach with the R^2 values of the original sample (with sample size=36) being 0.78, the size of validation set for the case of one parameter is obtained to be 08. Hence, 10 validation points, which were not included in deriving the regression models, formed the validation data set.

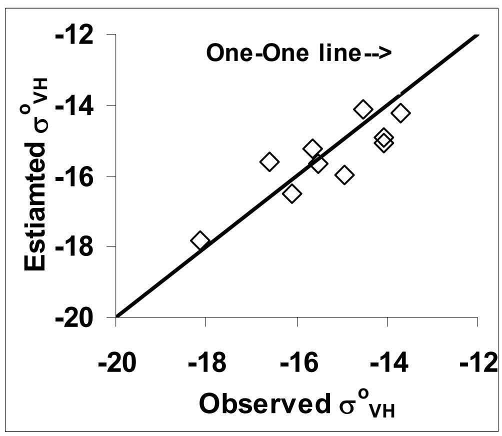

Fig. 3.: Scatterplot showing observed and estimated SAR backscatter values for validation data set.

Next, the validation of SAR backscatter from wheat field which was modelled using interaction factor of head (IF_{head}) was attempted. A validation data set consisting of 10 observations was used to arrive at estimated value of backscattering coefficient using the corresponding ground observation of the component wise interaction factors. Figure-3 shows the variation in estimated value of the backscattering coefficient for ten validation locations to the corresponding observed value of backscattering coefficient extracted from respective fields from the σ^o_{VH} images.

It can be observed from the scatterplot given in figure-3 that the modelled $\sigma^o_{VH(model)}$ is in agreement with the observed $\sigma^o_{VH(observed)}$. The rms error between observed and estimated σ^o_{VH} is 0.70 which is within the radiometric resolution of Envisat-1 ASAR. Thus the model developed in equation-12 is adequately able to characterise SAR interaction to wheat crop.

6.3 Retrieval of $IF_{(head)}$

Since the SAR backscatter model given in section 6.1 is reasonably validated, $IF_{(head)}$ can be retrieved by inverted the SAR backscatter model given by equation-12 using the following equation

$$IF_{(head)} = A' + B' * \sigma^o_{VH} \quad (13)$$

With the retrieved $IF_{(head)}$ one can make inferences on the upper layer of the canopy. A regression analysis was carried out, which resulted in the value of R^2 as 0.78 with F value being 125.83 (Significance of F= 6 E-13).

6.4 Modelling number of Grains from plants/m^2

A close observation of figure-4 (wheat head where number of grains can be clearly seen) reveals that one can actually

Fig. 4. A typical wheat head where space allotted for each of grains can easily be counted.

see the number space allotted for each of the grain and also one can actually count the number of grains that would be available from that plant. Hence the number of grains at this stage of crop is also directly related to the moisture content of the head and the volume of the head.

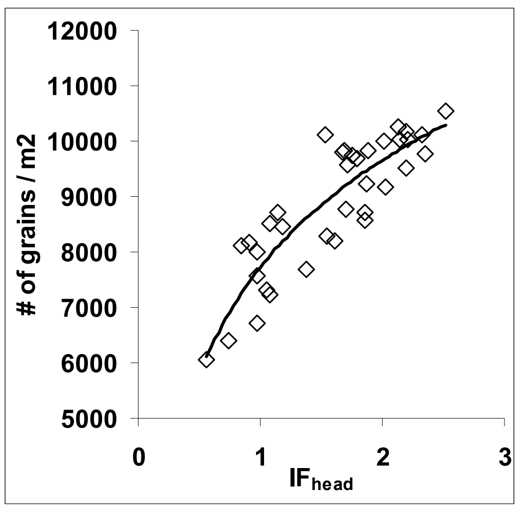

Fig. 5.: Variation of number of wheat grains per square meter with Interaction Factor of Wheat head.

To study the dependence of the number of grains on to the interaction factor of head, IF_{head} a scatter-plot showing the variation in number of grains with varying values of IF_{head} was studied as shown in figure-5. It was observed that a logarithmic curve represents the variation best. To retrieve the Number of grains from wheat plants/m^2, regression analysis was carried out to develop the relationship between the observed number of grains and the Interaction factor for head from the corresponding sampling location. The regression model relating the number of grains to the interaction factor of Head is given by:

$$\text{Grains} / m^2 = A + B * \text{Ln}\,(IF_{head}) \qquad (14)$$

The coefficient of determination (R^2) obtained in regression analysis was 0.77. Confidence level test using F statistic was performed for testing significance of the regression analysis, which yielded value of F =113.52 at level of significance of F = 2.24 E-12.

As has been observed from the results discussed in section 6.2, when the canopy is segmented in to three layers representing the interaction of SAR with three layers of the wheat canopy, SAR backscatter is influenced most by the upper layer of the canopy. Since we are interested in extracting information on the head of the wheat crop, firstly $IF_{(head)}$

is retrieved using equation-13, next the retrieved $IF_{(head)}$ is used for estimating the number of grains using the regression model given by equation-14 and the estimated grains are used to arrive at the yield of the sampling location with the help of average grain weight to accomplish the objective of modelling wheat yield.

6.5 Validation of the yield model

Since it is essential to validate the results arrived at by a statistical approach based analysis, the validation sample size was once again determined by the precision power approach as suggested by Brooks and Barcikowski [29]. The criteria

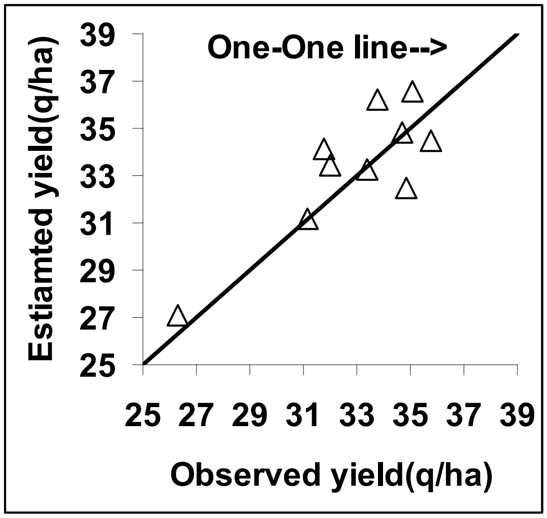

Fig. 6.: Scatter-plot showing observed and estimated wheat yield for 10 validation fields in (q/ha)

was that the sample correlation coefficient is not to decrease by more than .05 no matter what the expected value of correlation coefficient is. R^2 values of the original sample (with sample size=36) being 0.78 for the number of grains of wheat crop per m^2, the size of validation set for the case of one parameter is obtained to be 8. Hence the number of samples used for validation being 10 is more than that of the required sample size. In order to validate the results, estimated values of IF_{Head} were calculated using equation-13 for ten sampling fields which were not included for developing the model. The figure-6 shows the scatter plot between observed and estimated yield in (q/ha). The rms error values in terms of the percentage of observed values indicates that the error in estimating the wheat yield based upon the estimated number of grains arrived at by using equation-14 is of the order of 4.63 % (figure-7) of the observed value of the grains. The results of model validation are very encouraging and it indicates that it is feasible to model wheat yield in terms of number of grains using high-incidence angle cross-polarized SAR data.

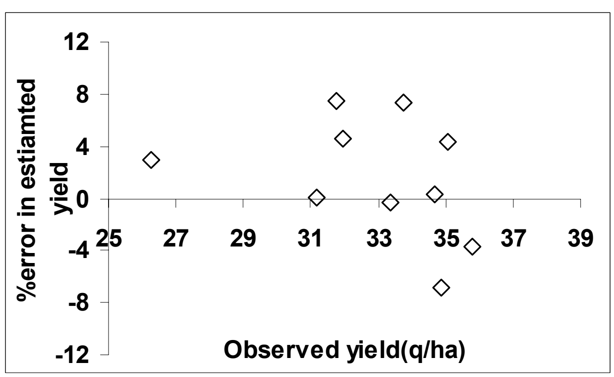

Fig. 7.: Percentage error in estimated yield for 10 validation fields

7. CONCLUSION

In this study an approach to model wheat yield in terms of estimating number of grains by exploiting the characteristic SAR interaction to the different layers of wheat canopy is presented. The wheat crop was segmented in to three components namely, head, leave and stem. In order to achieve the goal of estimating number of wheat grains that is physically related to the volume and moisture of the head of wheat plant, the interaction of SAR backscatter to the head of wheat canopy is studied. Firstly the SAR backscatter is modelled using Interaction factor of head of the wheat canopy. It is observed that cross polarised C-band SAR is significantly related to IF_{head}. The number of grains is retrieved using the inverted canopy descriptor parameter, namely IF_{head}. Finaly, wheat yield is calculated using the number of grains. The rms error value in terms of the percentage of observed values indicates that the error in estimating the wheat yield is of the order of 4.63% of the observed value of the yield which highlights the soundness of the approach. The significant outcome of the study is that it offers a direct approach to arrive at a very vital crop parameter that of number of grains by exploiting the interaction of cross polarised SAR with different components of wheat canopy by following a layered approach.

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