Crop Height Estimation Using RISAT-1 Hybrid-Polarized Synthetic Aperture Radar Data

Sugandh Chauhan, Hari Shanker Srivastava, and Parul Patel

***Abstract*—The objective of this paper was to explore the potential of hybrid-polarized (RH and RV) RISAT-1 SAR data to retrieve the height of wheat crop—an important winter crop in South Asian countries including India. The images acquired over north-west India in 2015 covered critical growth stages of wheat. The field campaigns were carried out in synchronous with the SAR passes. Considering the dominant role of underlying soil cover in the total backscatter (σ^0_{total}) response from a target, we propose that refining the σ^0_{total} by reducing the effect of underlying soil can significantly improve the retrieval accuracy of crop height (CH). To achieve this, we modified the existing water cloud model (WCM) to estimate soil-corrected vegetation backscatter (σ^0_{veg}). Leaf area index and interaction factor showed great potential as the vegetation descriptors in modeling σ^0_{total} using WCM. A comparative analysis between the CH retrieved from σ^0_{total} and σ^0_{veg} using multilayer perceptron neural networks revealed the response of *C*-band backscatter to CH. CH was moderately correlated to σ^0_{total}, but the results improved considerably with the substitution of σ^0_{total} with σ^0_{veg}. This holds true particularly in the early growth stages of crop growth when the vegetation cover is scarce and there is a substantial effect of soil background on the remote sensing signal. Thus, the results suggest suitability of *C*-band hybrid-polarized data for the assessment of CH.**

***Index Terms*—Artificial neural networks (ANNs), crop height (CH), interaction factor (IF), RISAT- 1, vegetation backscatter, water cloud model (WCM), wheat.**

I. Introduction

IN RECENT decades, the use of image-based remote sensing (RS) technology for crop height (CH) monitoring has gained momentum due to its capability to provide synoptic information in a timely and cost-effective manner [1]. In the context of precision farming, remotely sensed estimates of biophysical parameters, such as CH, together with crop growth models can be used to quantify crop yield [2]. For many cereals, CH is an essential indicator of current phenological stage [3], crop biomass, and yield. Therefore, its retrieval from RS can contribute to different application areas in crop monitoring.

The use of RS for CH estimation is generally challenging due to the structural heterogeneity of a crop canopy and contribution from the underlying soil surface, all of which affect the radar return signal. Several studies have highlighted the vast potential of radar data for CH estimation at different frequencies and polarizations [3], [4]. It is well known that SAR data acquired at shallow angle (>40°) shows relatively higher accuracy to height than low incidence angle (∼23°). However, except few [5], most of the previous studies have explored the sensitivity of satellite parameters derived from either dual (HH, HV, or VV, VH)/quad (HH, HV, VH, and VV) polarized data or interferometric (InSAR) data to estimate CH [6], [7]. Studies show that temporal decorrelation is the major limitation of InSAR technology, particularly over vegetated areas, where decorrelation increases with an increase in the vegetation cover. The perpendicular baseline of the interferogram can also affect the accuracy of height measurement. An increase in this baseline can reduce the standard deviation of height measurement.

Another possibility is that of using polarimetric data acquisition by hybrid polarimetric mode. In this mode, signal is transmitted at 45° linear mode or in the circular polarimetric mode and is received in horizontal as well as vertical polarisation. However, compared to the traditional SAR systems, application of hybrid-polarized systems for the crop monitoring have been limited. RISAT-1 provides hybrid-polarity SAR system that transmits a circularly polarized signal, and the resulting signal is received in two mutually coherent orthogonal polarizations. The primary drawbacks of traditional fully polarimetric SAR systems are lower swath widths and increased hardware complexities due to increased pulse repetition frequency (by a factor of two) and data rate (by a factor of four) [8]. Most of the work, however, has focused on four major applications areas: RISAT-1 radiometric calibration [9]; land cover classification [10]; crop biophysical parameters retrieval [11]; and crop type mapping [12]. Uppala *et al.* [13] presented preliminary results on the role of Raney m-δ, m- χ decompositions of a single date RISAT-1 data for discrimination of rice crop. However, except few studies, the usefulness of hybrid polarimetric data from RISAT-1 for crop biophysical parameter retrieval has been less explored. It is well-known that soil background acts as noise in crop biophysical parameter retrieval applications and constrains the accuracy of the retrieval process. Brown *et al.* [14] and Mattia *et al.* [15] suggest that particularly in *C*-band, the contribution from underlying soil attenuated by the canopy above

Manuscript received September 28, 2018; revised March 8, 2019; accepted May 10, 2019. Date of publication July 8, 2019; date of current version September 16, 2019. *(Corresponding author: Hari Shanker Srivastava.)*

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Digital Object Identifier 10.1109/JSTARS.2019.2919604

dominates the backscatter response in case of narrow leaf crops such as wheat. The effect is more pronounced in early growth stages when the percentage of vegetation cover is low. In this paper, we propose a new methodology for the retrieval of CH that eliminates the effect of the underlying soil, giving us pure vegetation backscatter. Modeling SAR backscatter from vegetated surfaces can be challenging. Semiempirical models such as the water cloud model (WCM) based on first-order radiative transfer theory have proved to be a good compromise between the empirical and theoretical modeling approaches [16]. The simplicity of the WCM, however, comes at the cost of a low degree of accuracy due to many assumptions and simplification. Therefore, we propose a modified WCM that accounts for the heterogeneity of crop structure and distribution of plant water within plant volume.

In this paper, CH is estimated using artificial neural networks (ANNs), a powerful nonlinear inversion method, with the inputs generated from satellite images and modified WCM. The objective is to compare the retrieval accuracy of CH from total backscattering coefficients ($\sigma^0_{\mathrm{total}}$) and vegetation backscattering coefficients (σ^0_{veg}).

II. Study Area and Datasets

A. Study Area

The investigation was carried out over the parts of Bharatpur and Mathura districts located in Rajasthan and Uttar Pradesh (India), respectively. The study area falls in the agro-climatic zone of flood prone eastern plain region and experiences mostly hot semiarid (drier half) climate. Climatically, the region being dry becomes extensively hot in summers (March–June) and cold in winters (December–Februrary). The region is characterized by rich alluvial soils with wheat and mustard being the major crops. Wheat is sown once in a year from late November to early December and is harvested in April. Most of the fields are greater than 600 m^2 in the area.

B. RISAT-1 Data Acquisition and Processing

During the field campaign (January 27, 2018–March 2015), three single look complex RISAT-1 images acquired over the study area were provided by the National Remote Sensing Centre, Hyderabad, India. In this paper, we focused only on the circular RH and RV polarizations. The data was obtained in fine resolution stripmap (FRS-1) mode with the spatial resolution of 3×2 m and incidence angle of $\sim 38°$. The backscatter images were georeferenced (in ENVI 4.3) with 120 GCP's to match with the base geometry. A second order polynomial transformation with the nearest neighborhood sampling approach was applied. The related root-mean-square error (RMSE) was approximately 0.87 pixels. Once georeferenced, the three-date RH and RV backscatter images were coregistered. For speckle suppression, an enhanced Lee filter with the moving window of 3×3 was applied to the images. For each polarization image, the mean backscatter coefficient $\sigma^0_{\mathrm{total}}$ values were extracted using the ENVI 4.3 software.

TABLE I
Summary of the Field Measurements Collected During January–March 2015

Crop/soil variables	Max.	Min.
Crop variables		
LAI (m^2/m^2)	6.12	0.25
PWC (kg/m^2)	4.00	0.46
Plant density (per m^2)	652	220
Crop Height (m)	1.00	0.30
Plant Volume (c.c. /m2)	20.5	2.94
Wet Biomass (kg/m^2)	5.00	0.61
LWAI *(unitless)*	33.92	1.37
IF *(unitless)*	46044	1607
Soil variable		
Volumetric soil moisture (%)	40.00	10.12

C. Field Data Collection

Coincident with the RISAT-1 overpasses, the ground survey was carried out covering three growth stages of wheat; end of tillering (late-January), early heading (mid-February) and early grain-filling (mid-March) stage. A total of 220 samples (140 from wheat and 80 from bare fields) were collected throughout the growth cycle of wheat. The statistical approach suggested by Patel and Srivastava [17], which considers the fading phenomenon, was used to determine the size of the sampling unit, minimum number of pixels *(m)* to be averaged and the sample size for model development and validation. Considering the error of 10% with 95% confidence interval on the signal amplitude, the value of *m* (number of pixels) and minimum sampling unit size in m^2 was estimated to be 105 pixels and 630 m^2, respectively, while at least 11.4 samples had to be used for model validation. Table I enlists the soil and crop parameters that were collected during the field campaign along with their maximum and minimum values.

The soil samples were collected at a depth of 0–5 cm using core samplers to measure volumetric soil moisture. Within each field, five small plots (1×1 m) were established, and the observations were recorded from each plot and averaged. The plant water content (PWC) was determined by weighing destructively sampled wet and dry biomass. Leaf area index (LAI) was measured using an AccuPAR LP-80 PAR/LAI Ceptometer. For measuring plant volume, the plants were immersed in graduated measuring cylinders and the amount of water displaced was measured. A measuring tape was used to record CH and plant density. The mean height of wheat ranged from $\sim$30 to 100 cms, with maximum height during grain heading. The increasing trend in CH is mainly due to the continuous elongation of the crop stem and simultaneous growth of the spikes.

III. Methodology

To retrieve CH over the wheat growth cycle, a method based on the combination of semiempirical WCM and ANN is proposed. It consists of the following three steps.

1) Parameterization of WCM (2) to determine the coefficients (A, B, C, D) and the best set of canopy descriptors (V_1 and V_2).
2) Estimation of σ^o_{veg} for each polarization $\sigma^o_{V\_\mathrm{RH}}, \sigma^o_{V\_\mathrm{RV}}$.

TABLE II
VALIDATION OF TOTAL RH AND RV BACKSCATTER SIMULATION USING WCM FOR DIFFERENT TEST CASES

V_1	V_2	R^2	RMSE (dB)	
LAI	LAI	0.55	2.21	RH
LAI	PWC	0.67	2.10	
LWAI	LWAI	0.72	1.81	
LAI	IF	0.90	1.18	
LAI	LAI	0.40	3.53	RV
LAI	PWC	0.69	2.02	
LWAI	LWAI	0.72	1.93	
LAI	IF	0.85	1.25	

3) Retrieval of CH with ANN using $\sigma^o_{V\_\mathrm{RH}}, \sigma^o_{V\_\mathrm{RV}}$ and $\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$.

The WCM developed by Attema and Ulaby [18] describes a vegetation canopy as two layers: vegetation and soil. In the presence of vegetation, $\sigma^o_{\mathrm{total}}$ is a resultant of surface scattering (σ^o_{soil}), volume scattering of the vegetative elements (σ^o_{veg}) and the volume- surface scattering ($\sigma^o_{\mathrm{soil\_veg}}$). In this paper, we have neglected the volume-surface interaction term since the formulation depicts a first-order solution of the radiative transfer equation across a weak medium. The general expression of the model is as follows:

$$\sigma^o_{\mathrm{total}}\ (dB) = \sigma^o_{\mathrm{veg}} + L^2\ .\ \sigma^o_{\mathrm{soil}} \tag{1}$$

$$\sigma^o_{\mathrm{total}}\,(dB) = \{A.V_1.\cos\theta_i\,[1-\exp(-2B.V_2.\sec\theta_i)]\} + \exp(-2B.V_2.\sec\theta_i).\ (C + D.M_v) \tag{2}$$

where L^2 is the two-way attenuation factor; A and B are the vegetation specific coefficients; C and D are the soil specific coefficients; V_1 and V_2 are canopy descriptors; θ_i is the incidence angle; and M_v is the volumetric soil moisture.

A. Parameterization of the WCM

The parameterization of the WCM consists of estimating unknown coefficients A, B, C, and D for a given set of canopy descriptors V_1 and V_2 to enable simulation of $\sigma^o_{\mathrm{total}}$. To estimate the σ^o_{veg} using WCM, we tested four combinations of different canopy descriptors (V_1 and V_2): LAI, PWC, leaf water area index (LWAI), and interaction factor (IF).

LAI, one of the most widely used canopy descriptors, characterizes the vegetation density with respect to the leaf size that effectively participates in weakening the backscatter over the vegetation [19], [20]. PWC is obtained by the difference between the wet biomass (WB) and dry biomass (DB). LWAI or the quantity of water extended in the leaf area is obtained by multipying LAI with (WB-DB)/DB.

While the performance of these descriptors is well documented for linear copolarizations (HH or VV) [20], [21], same inferences cannot be drawn for circular polarizations (e.g., RH or RV). Hence, a detailed analysis was performed to understand the sensitivity of plant height to circular polarizations. The underlying assumption of WCM states that the water droplets are distributed homogeneously throughout the crop canopy. This, however, does not hold well for the real field conditions. IF, on the other hand, is a novel plant parameter conceptualized by Patel *et al.* [22]. IF accounts for the distribution of PWC within crop volume and its formulation is as follows:

$$\mathrm{IF} = \frac{(\text{Plant moisture} * \text{Volume of plant} * \text{Plant density})}{\text{Plant height}}. \tag{3}$$

Prevot *et al.* [23] proposed the soil parameters C and D were determined using the independent observations of volumetric soil moisture from bare fields (0–5 cm layer). Assuming that the $\sigma^o_{\mathrm{total}}$ comprised of the contribution from bare soil only ($\sim\sigma^o_{\mathrm{soil}}$), a linear equation was fitted and the values were determined. Subsequently, for estimating A and B, a cost function was iteratively minimized. Levenberg–Marquadt optimization technique was used to estimate the coefficients since it combines the advantages of steepest descent and Gauss–Newton method. The parameterization that modeled $\sigma^o_{\mathrm{total}}$ with the highest accuracy was then used to calculate σ^o_{veg}.

B. Artificial Neural Networks

Two ANN architectures: $\mathrm{NN}_{\mathrm{total}}$ ($\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$ as inputs) and $\mathrm{NN}_{\mathrm{veg}}$ ($\sigma^o_{V\_\mathrm{RH}}, \sigma^o_{V\_\mathrm{RV}}$ as inputs) were created to estimate CH. The workflow of configuring ANNs comprises four steps: Preparing data; creating and training network; posttraining analysis; and implementation.

Preparing data sets for training, validation, testing (TVT), and independent simulation is the most crucial step and dictates the ultimate performance accuracy of a network. Using a random sampling procedure, we set aside 12 points for independent validation. The remaining points were then divided into 80%–10%–10%, respectively, for TVT process. A standard feedforward multilayer perceptron network was created in MATLAB using NN toolbox and manual scripting capabilities. The network was trained with different training subsets to determine the optimum subset that was representative of the whole sample data. The network was trained once the RMSE for CH was within the permissible limits. A trial and error method determined two crucial parameters; the hidden layer size and training function. In our case, a single hidden layer provided reasonable results.

The trained networks were evaluated by analyzing the performance graphs and regression plots. In case any overfitting had occurred, the training process was repeated. Once the networks were trained and validated, they were used to estimate the output for independent validation dataset (12 points) and the error statistics: RMSE, mean absolute percentage error (MAPE), and index of agreement (IA) were calculated.

IV. RESULTS

A. Performance of the WCM

With the fundamental aim of understanding the response of backscatter and elucidating its relationship with CH, $\sigma^0_{\mathrm{total}}$ was refined using WCM. A regression analysis of volumetric soil moisture measurements (M_v) from bare fields with

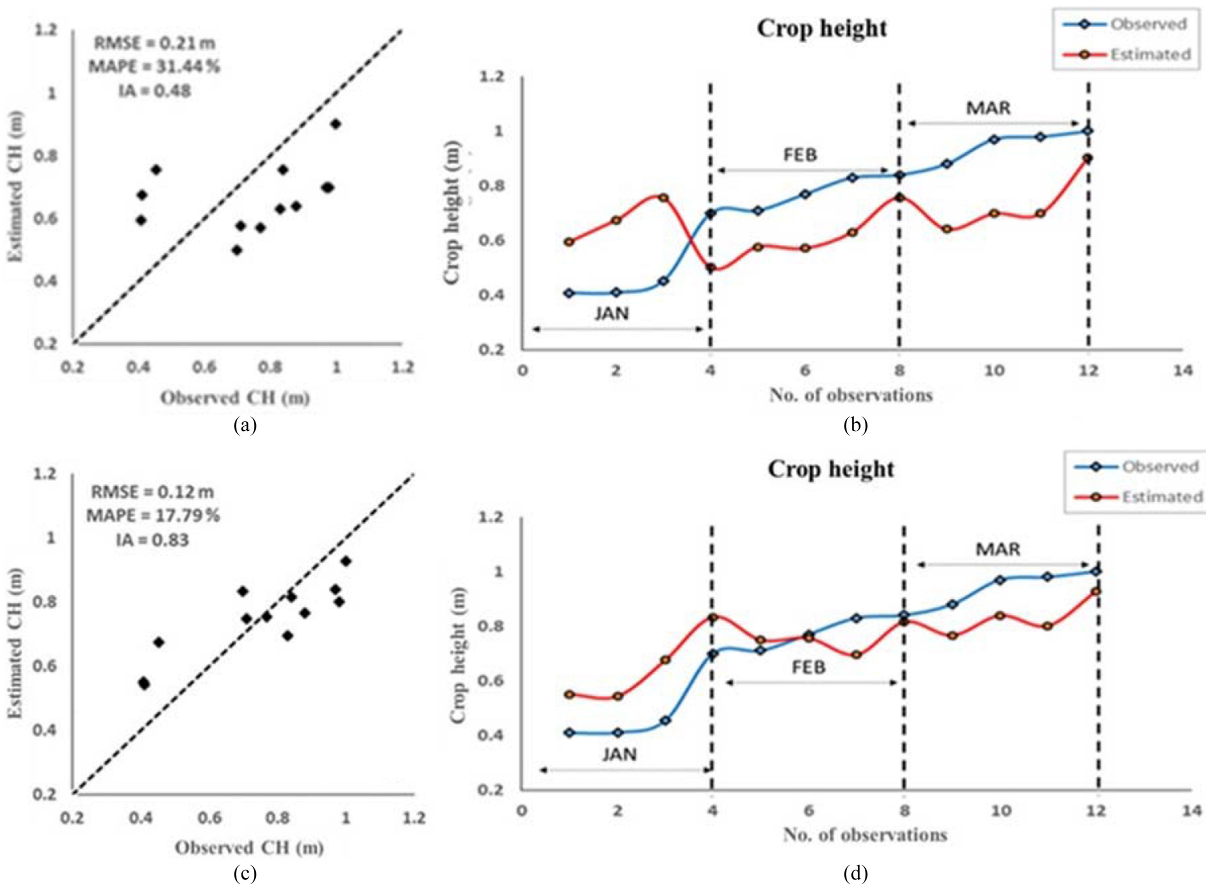

Fig. 1. (a) and (c) Scatter plot. (b) and (d) Variation of observed and estimated CH across the season *(Number of samples* $N = 12$*)* using $\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$ and $\sigma^o_{V\_\mathrm{RH}}, \sigma^o_{V\_\mathrm{RV}}$, respectively.

$\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$ was performed to estimate C and D coefficients (2). A reasonable coefficient of determination (R2) was observed between $\sigma^o_{T\_\mathrm{RH}}$ $(R2 = 0.71)$, $\sigma^o_{T\_RV}$ $(R2 = 0.70)$ and M_v for all the sampling points. The results corroborate the fact that $\sigma^o_{T\_\mathrm{RH}}$ and $\sigma^o_{T\_\mathrm{RV}}$ are more or less equally sensitive to M_v. The soil moisture sensitivity factor D was estimated as 0.285 and 0.278 for RH and RV, respectively, while the parameter C came out to be -19.914 and -23.168, respectively.

To model the backscatter from the vegetation, two canopy descriptors; V_1 and V_2, are used in WCM. It is assumed that these two descriptors, along with other coefficients (A, B, C, D) and variables (such as incidence angle), are capable of fully characterizing the backscatter from the target under consideration. This is done to simplify the backscatter simulation and reduce the dimensionality of input data to WCM. Nevertheless, quite satisfying test results were achieved, generating some significant findings.

LAI alone was unable to model $\sigma^o_{T\_\mathrm{RH}}$ and $\sigma^o_{T\_\mathrm{RV}}$ since it could only characterize the density of the canopy cover in terms of the leaf size. LAI and IF, however, outperformed the other test cases with the highest R2 (0.90 and 0.85) and IA (0.80 and 0.86) values for both $\sigma^o_{T\_\mathrm{RH}}$ and $\sigma^o_{T\_\mathrm{RV}^o}$, respectively. The IF amalgamates the effect of plant density, plant volume, PWC, and plant height into one discrete form, thus characterizing the distribution of moisture within a confined volume. The R^2 and error statistics for each case are summarised in Table II. For more elaborate results on the four test cases of canopy descriptors and other coefficients, the reader is referred to [24]. After careful validation, the parametrization with $V_1 = \mathrm{LAI}$ and $V_2 = \mathrm{IF}$ was chosen to retrieve σ^o_{veg} for all sampling locations.

B. Retrieval of CH

A preliminary analysis of the relationship between ground measured CH, and satellite/WCM derived measurements confirmed its sensitivity to the *C*-band radar backscatter data. The ANN networks were trained rigorously, such that a proper combined effect of multi-polarized RH and RV backscatter data was tested.

1) Retrieval of CH From Total Backscattering Coefficients: Among the several structures and networks tested, feedforward neural network trained by gradient descent with momentum backpropagation training algorithm mapping could be created between input RH, RV backscattering coefficients, and CH. The CH was retrieved from both $\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$ and $\sigma^o_{V\_\mathrm{RH}}, \sigma^o_{V\_\mathrm{RV}}$, respectively, and the (traingdm) performed reasonably well. The threshold of RMSE for the calibration dataset was kept as 0.20 m, implying that the network was considered trained once the RMSE dropped to <0.20 m. The number of nodes in the hidden layer was fixed as 17 since the network performance saturated with any further increase.

However, with $\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$ as input, the estimated CH values were quite off the 1:1 line. The R^2 was substantially low (0.60) with the RMSE of 0.21 m and MAPE of 31.44%. A closer look at Fig. 1(a) reveals that CH values were highly over or underestimated by the network, as it could not generalize the relationship between input-output pairs.

2) Retrieval of CH From Vegetation Backscattering Coefficients: The model performance modestly improved with $\sigma^o_{V\_\mathrm{RH}}, \sigma^o_{V\_\mathrm{RV}}$ as input. The feedforward network with Bayesian regularization (BR) training algorithm (*trainbr*) and 2-16-1 configuration gave optimum results. The overall R^2increased to 0.68, and the RMSE and MAPE dropped by almost 43% and 14% in comparison to the previous case, indicating the superiority of this model over the other one. This is evident from the Fig. 1(c) where the horizontal axis represents the target (or observed) CH values while the vertical axis is the CH estimated by $\mathrm{NN}_{\mathrm{veg}}$. Except for a few points, a majority of them fall in the vicinity of 1:1 line while those in Fig. 1(a) are more scattered.

V. Discussion

The model developed using $\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$ as input highly overestimated CH, especially in the early growth stage, as it tended to measure the attenuated soil backscatter too [see Fig. 1(b)]. The prediction was, however, highly underestimated in the subsequent stages. The trajectory followed a similar trend in the second case [see Fig. 1(d)], but with a moderate improvement since the model was refined by reducing the effect of dominant backscatter of the soil cover. The shift was somewhat subdued.

It is known that the vegetation canopy, which is itself a volume of scattering constituents, is bounded by a scattering soil surface. Particularly in *C*-band, the $\sigma^0_{\mathrm{total}}$ obtained from the SAR data is the resultant of the contribution of both vegetation and underlying soil cover. Furthermore, the attenuation of the radar signal from soil increases with the incidence angle. During the retrieval of crop biophysical parameters (such as CH), the underlying soil cover acts as noise and has to be eliminated. The effect of soil is higher in the early growth stages (CH < 0.3) when the canopy is shorter and less dense with more soil exposed. It is important to note here that high R^2 do not always imply direct mechanistic relationships. Indirect or superficial relationships can result in lower accuracy levels and may constrain wider applicability. CH was found to be moderately correlated with the hybrid-polarized RH and RV, but the relationship was presumed to be more indirect and superficial since the scattering processes do not directly influence height. The superficial sensitivity of backscatter to CH can be attributed to the changes that occur in leaf biomass and canopy structure and is highly dependent on the relationship between CH and canopy structure. In this paper, we found that CH did not have a consistent relationship with the backscatter at each phenological stage. Thus, the variations in CH at similar growth stages are quite difficult to detect using backscatter values alone, especially with a single angle of incidence.

VI. Conclusion

In this paper, we have presented a novel approach for the estimation of CH from hybrid polarized RISAT-1 SAR data. We modified the existing WCM to model the radar backscatter and estimate soil-corrected vegetation backscatter from wheat fields. The approach is relatively accurate and simple for its application to CH retrieval using the radar backscatter information alone from vegetated fields. We focused on four different combinations of canopy descriptors to understand the scattering mechanisms and develop a simple scattering model for wheat. The results of the analysis of canopy descriptors were used to modify the existing WCM. The evidence from this study suggests the ability of LAI and IF crop parameters to represent the crop heterogeneity.

Furthermore, ANN proved to be highly efficient in retrieving CH. The comparative analysis of the retrieval accuracy of CH from $\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$ and $\sigma^o_{V\_\mathrm{RH}}, \sigma^o_{V\_\mathrm{RV}}$ revealed interesting results. The CH was found to be moderately correlated to $\sigma^o_{T\_\mathrm{RH}}, \sigma^o_{T\_\mathrm{RV}}$ with an R2 of 0.60, which increased considerably to 0.68 when the input was substituted with $\sigma^o_{V\_\mathrm{RH}}, \sigma^o_{V\_RV}$. These findings add to a growing body of the literature on our understanding of scattering mechanisms from crops and retrieval of crop biophysical parameters. The relationship between CH and backscattering coefficients is, however, superficial and indirect, explaining the overall lower coefficient of determination. These findings suggest following opportunities for future research: Exploring the use of decomposition algorithms (for hybrid-polarimetric data) to better understand the scattering from wheat and employing more rigorous radiative transfer models (second-order) for CH retrieval. Nevertheless, this paper is the first step toward enhancing our understanding of the response of hybrid-polarized data to wheat CH.

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