RETRACTED ARTICLE: Estimating snow depth Inversion Model Assisted Vector Analysis based on temperature brightness for North Xinjiang region of China

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ABSTRACT

The measurement of snow depth based on temperature brightness with passive microwave sensing is still a challenging problem. Snow depth for the snow cover hydrological model and climate model is a significant input parameter. Hence, this study concentrates on Inversion Model Assisted Vector Analysis (IMAV) for estimating snow depth in north Xinjiang based on the brightness of temperature. Further, the estimated set of IMAV has been hybridized to address the problem. The results suggested that for both horizontal and vertically polarized PMW radiation the IMAV outperforms SVM at 11.05, 19.6, and 38.4 GHz. If the root mean square error (RMSE) in the IMAV performance is 8 K or below, compared with anormal SVM calculation, then the average over the nine-year study period across the North Xinjiang region of China, the failure correlation coefficient is 7 or greater. Compared with SVM tests, the RMSE was decreased by more than 17% for any of the six frequencies and polarization combinations evaluated, while the anomaly coefficient was raised by more than 50%. Such results suggest that the IMAV is an superior alternative to the SVM for subsequent use in ad data assimilation system as an calculating operator.

Discussion on snow depth based on temperature brightness

Snow is an important element of the hydrological cycle, accounting for a considerable portion of the freshwater resources available throughout many parts of the Northern Hemisphere of China. North Xinjiang province is a major agricultural district in China, with snow cover as the area’s largest aquifer as shown in Figure 1. Continuous and extreme snowfall in winter and spring may contribute to hazards (Dai et al., 2012) (for example, frostbite or death of livestock), or severely restrict the productive use of local wildlife. Snow also provides more than 1 billion people worldwide with a dominant source of freshwater. Rapid snowmelt in spring also contributes to flood outbreaks with serious effects on grassland cultivation in low-level areas. Therefore, it is not only necessary to monitor the depth and extent of snow cover for research on hydrology and climate change, but it is important to also monitor farmers’ production and livelihoods. When using a land model in the process, the corresponding model state variables need to be projected into the corresponding measurement area (X. Wang et al., 2008).

In the snow data assimilation, snow model legislative variables including SWE in a physically dependent radioactive transmitting mode which can be used as a mapping factor in passive microwave (PMW) light room. The climatic changes and snow cover as well as snow density level of China are shown in Figure 2. Direct quantification of the snow density, or the snow water equivalent (SWE) (T. G. Liang et al., 2008), is made difficult however by considerable space and time variation, which ensures that the spatiotemporal complexity of SWE cannot be identified by the small, ground-based observation networks often. In addition, scientists also launched to use space-based tools in accordance with land surface modelling (LSMs). Data integration can be utilized to combine orbital measurements with physical or in-site assessments (X. Wang et al., 2009) by measuring the differences in each, to generate a combined result better than the individual estimates. Hence, the low microwave space resolution, the complex characteristics of the soil pixels and the changes in snow status over time and space which make it difficult to invert equivalent snow water need further investigation.

However, it is well recognized that habitat effects that limit PMW pollution from underlying snow can hinder the capacity in areas with significant deforestation to estimate SWE. The integration of measurements of PMW brightness temperature ($B_T$) is an option to assimilating PMW, SWE extraction (X Huang et al., 2011). IMAV approach focuses on estimating snow depth in north Xinjiang based on the
brightness of temperature. Furthermore, in this paper, IMAV has been hybridized and the mathematical model has been given out to perform IMAV at 11.05, 19.6, and 38.4 GHz. The RMSE of IMAV has been decreased by more than 17% for any of the six frequencies and polarization combinations evaluated, while the anomaly coefficient was raised by more than 50%. The rest of the paper is organised as follows: part 2 review on related work, part 3 insights regarding our proposed IMAV approach, part 4 mathematical model for snow depth estimation based on temperature brightness part 5 the findings of the study related to IMAV work. Finally, the paper closes with its conclusion and future scope.

**Background study on snow depth model based on temperature brightness**

The author (Chang et al., 2009) discussed the mathematical model that has the effect of snow cover region of high frequency (89.0 GHz) in the exactness of the inversions and on the basis of Chang’s classically utilized method for the calculation of snow depth in China. The results show that the exact snow depth inversion in China can be improved by modern reversal algorithms. Furthermore, the low space microwave resolution, complex characteristics in the ground pixel, and snow state changes over time and distance, which make it difficult to invert equal snow water, are
important to study further. The author (Yang et al., 2019) proposed four algorithms WESTDC, AMSR-E, Chang algorithm, Foster algorithm. Validation results show WESTDC performs better than others among these algorithms. Such two algorithms sometimes contribute to significant deep snowpack (over 20 cm) underestimation, while the other three tend to overestimate snow depth, likely due to their poor snowpack output in China. The mathematical model has been developed for a snow depth retrieval algorithm appropriate for satellite images to solve retrieval bugs that exist under deep snowpack conditions. This paper (Che et al., 2004) illustrates an optimal method for recovery of forest transfer rates of 18 GHz and 36 GHz used in field experiments. Snowpack’s (MEMLS), a dynamic (LUT) was introduced to forestry transmissions and snow characteristics. The end result of the proposal method is: 1) the effects of forests on the recuperation of SD are significant and the correct forest parameters should be taken into account when calculating a snow depth using PMW temperature data and 2) the algorithm for the recuperation of snow depths based on a dynamic LUT method in north-eastern China is successful. (Che et al., 2016) The author discussed the priori model for snow characteristics, including height, density and temperature of the snowpack, a modern snow depth/water equivalent (SWE) algorithm is suggested for the extraction of passive microwave brightness temperature. SWE algorithm considerably reduces the root average squared error (RMSE) (Dai et al., 2012) compared to NSIDC, slightly decreased compared to ESA, WESTDC. To overcome all these drawbacks, the IMAV approach mainly focuses on estimating snow depth in north Xinjiang based on the brightness of the place. Input parameters for the proposal method is given in equation 3

\[ B_T = tB_{T\text{place}} + t(1 - e_{\text{place}})T_{\text{space}_l} + T_{\text{space}_l} + T_{\text{natural}}t^2(1 - e_{\text{place}}) \]  

where \( t \) is the place transmissivity. \( T_{\text{space}_l} \) and \( T_{\text{space}_l} \) are up levelling and down levelling temperature brightness of the place. Input parameters for the

### Inversion Model Assisted Vector (IMAV) for snow depth analysis based on temperaturebrightness-mathematical model

An input vector \( X \) is considered as \([1 \times m]\), where \( m = 12 \) are the remote sensing variables, which are given at a location to characterize the snow and surface conditions in time and space. Land surface modelling is used to derive the input vector \( X \) (Forman et al., 2014). Upon training on \( B_T \) measurements (Forman & Reichele, 2014), a non-linear IMAV can be used to predict the estimated \( B_T \) feature at a specified frequency and polarisation in space and time for a given location can be modelled from equation 1,

\[ f(X) = \sum_{j=1}^{n}(\lambda^j - \lambda)H(Y_j, X) + \psi \]  

\( n \) is the number of training targets (measurements for various locations, frequencies and polarization are given by \( B_T \))

\( \lambda \) and \( \lambda^* \) are the \([n \times 1]\) set of dual Lagrangian multipliers

\( \psi \) is bias coefficient

\( H(Y_j, X) \) is the kernel function which is based on the radial basis as given in equation 2

\[ H(Y_j, X) = \exp\left(-\gamma\|Y_j - X\|^2\right) \]  

\( Y_j \) is the training matrix which can be represented in the form of \([n \times m]\) matrix, collection of \( n \) input vector \( Y_j \) at the time of \( n \) training targets. During preparation, \( \lambda, \lambda^*, \psi \) variables are described (Li et al., 2012), together with the corresponding support vectors.

It should also be remembered here that \( (Y, X) \) are determined with the same LSM but that both sets have different time periods and can thus be considered distinct. After the approximating method is defined (X. D. Huang et al., 2007) and the training for the IMAV is done, (1) offers a simple, computer-cost way of estimating \( (B_T) \) as a function of time, given time conditions that vary from the LSM simulation in near-surface terms.

### Snow modelling and brightness temperature

A semi-empirical microwave pollution concept is the IMAV snow model. (Ye et al., 2012) The main objective of the development of the model was to keep the number of parameters low and to ensure its applicability to inversion satellite data. (Che et al., 2004) Their results are based on radioactive transmission equations and measurements in Finland and Switzerland. (Xie et al., 2009), (Li et al., 2012) The model has two fundamental assumptions: 1) a standard snow sheet and 2) microwave radiation is primarily distributed to the forward face. The first theory does not typically occur in natural snow packs where heavy snowfall, and refrigeration processes and a dense hoar create layers again and again. In comparison, the calculated parameters profiles are rarely present, even modelling studies have to be applied for the average or even the values predicted for the whole snowpack. Furthermore, the profiles calculated at one location do not represent the entire satellite pixel over tens of kilometres. However, the IMAV snow model worked well in comparison to other snow models as shown.

The IMAV climate model measures the snow-covered temperature measured from space and the representation of the model is given in equation 3
IMAV snow model are various: snow temperature, kernel scale, SWE, density, bulk moisture, and salinity. The grain size effect is based on the extinction factor and can be given in equation 4

\[ R_e = 0.0019 f^{0.6} d^2 \]  \hspace{1cm} (4)

\( R_e \) is the extinction in decibels. \( f \) is the frequency in gigahertz and \( d \) is the diameter of grain in millimetres. \( R_e \) is used for finding the size of a grain.

The IMAV model algorithm mainly uses light temperature and physical surface (\( T \)) data for the 11, 19, 24, 37 and 88 GHz average (Tiangang et al., 2007). The comparison is made between snow cover, dry and rainy snow and no snow as shown in Figure 3. The modelling of IMAV involves the following steps:

**IMAV algorithm**

Step 1: Dry and rainy snow/snow cover needs to be separated. If it is dry snow requirement (1) is met other than the requirement (2), the flow chart directly moves to step 2

\[ B_{T37\text{horizontal}} < 265K \]

\[ B_{T37\text{vertical}} < 275K \]

Step 2: moderate and deep snow need to be separated from shallow snow. If either of the requirements (3) or (4) is met it will move to step 4. If it is a shallow snow cover it will go to step 3

\[ B_{T11\text{horizontal}} - B_{T37\text{horizontal}} > 0K \]

\[ B_{T11\text{vertical}} - B_{T37\text{horizontal}} > 0K \]

Step 3: Identify a snow cover that is small. Once requirement (5) is met, it is snow-coated, and the SD is calculated to be 5.02 cm.

\[ B_{T88\text{horizontal}} < 275K, B_{T88\text{vertical}} < 275K \]

Step 4: For mild to deep snow cover, snow density can be measured by the following step.

\[ \text{Snow density} = \frac{1}{\log_{10}} \left( \frac{B_{T37\text{vertical}} - B_{T37\text{horizontal}}}{B_{T11\text{vertical}} - B_{T11\text{horizontal}}} \right) \times \left( \frac{B_{T19\text{vertical}} - B_{T19\text{horizontal}}}{B_{T11\text{vertical}} - B_{T11\text{vertical}}} \right) \]

The earth bare soil model for snow-covered land simulation and the extraction of geophysical parameters from satellite knowledge has been shown in Figure 4 and established at the time with the IMAV snow model. The goal was to create a simple model with few but wide-ranging parameters. (Fu et al., 2007) The model is semi-empirical and focuses on soil sample measurements between 1 and 110 GHz.

The reflectivity behaviour on vertical (V) polarization is based on the horizontal (H) polarization results because of a more problematic V polarizing modelling of flexibility.

The equations for rough bare soil for reflectivity are given in Equation 5 and 6

\[ r_{H,\text{model}} = r_{H,F}.\text{EXP}\left\{ - \left( Wa \right)^{0.11\cos\theta} \right\} \]  \hspace{1cm} (5)

\[ r_{V,\text{model}} = r_{H,\text{model}} \cdot \left( \cos \theta \right)^{0.7} \]  \hspace{1cm} (6)

\( W \) is the wave number, \( r_{H,F} \) is the (H) horizontal polarization of the Fresnel reflectivity, a is the surface height and \( \theta \) is the angle of incidence.

**Soil modelling**

![Figure 3. Comparison of snow cover, dry and no snow.](image)
The output from IMAV with $B_T$ at 11.05 GHz, 19.6 GHz, and 38.4 GHz at vertical and horizontal polarization is shown in Table 1.

### Forest modelling

The IMAV forest Model is strictly observational and is based on the calculation of snow-covered trees (C. H. Wang et al., 2009). The major part of forest snow depth study has been carried out in Xinjiang, northern part of China. Only the steps on the V-polarization are based on the final model used here. The forest modelling calculating the transmissivity $G$ and the stem volume used for vegetation $S$ is explained in equation 7

$$G(H, S) = G(H, S_{high}) + \left[ 1 - G(H, S_{high}) \right] e^{-0.025}$$

$$G(H, S_{high}) = 0.32 + (1 - 0.32).e^{-0.025.\frac{h}{c}}$$

$G(h, S)$ is the forest modelling, H horizontal polarization.

Consider $[l \times k]$ training matrix $x$, [l x 1] is the training targets of $z$ with $(x_1, v_1) \ldots (x_l, v_l)$. In matrix analysis, the geophysical variables $x$, that describe snow and near-surface conditions at a given location and at different times from the LSM simulation are described. (Ye et al., 2012) A series of satellite $l$ measurements of PMW at a given frequency $B_T$ and polarization are presented in the vector $v$. Assume that the geophysical inputs $\theta(y)$ from LSM are mapped into space $B_T$ as shown in Equation 9

$$H(Y, \epsilon) = \langle Y \cdot \epsilon(z) \rangle + \omega$$

$Y$ is a weight of vector, $\langle Y \cdot \epsilon(z) \rangle$ is the inner dot product of $Y$ and $\epsilon(z)$ and $\omega$ is bias coefficient. $A > 0$ and $\omega > 0$ are the parameters and nonlinear vector regression basic model is given in Equations 10 and 11

$$\text{minimize } \frac{1}{2}(y - y_0)^2 + \frac{n}{2} \sum_{j=1}^{n} (\epsilon_j + \epsilon^*_j)$$

Subject to $\langle Y \cdot \epsilon(z) \rangle + \omega - v_j \leq \omega + \epsilon_j$

$$v_j - Y \cdot \epsilon(z) - \omega \leq \omega + \epsilon^*_j$$

$$\epsilon_j, \epsilon^*_j \geq 0, j = 1, 2, \ldots, n$$

Here $n$ is the number of time calculations necessary (for a certain space location); $v_j$ is $B_T$ measurement of time $i$, $\epsilon_j, \epsilon^*_j$ are stack variables. (Zhengan, 2000) The values of $\omega, \epsilon_j, \epsilon^*_j$ are not a priori defined but are decided by the minimization process. The goal of the minimization phase is to define values for $\omega, \epsilon_j, \epsilon^*_j$ and as to ensure that the mapped inputs are more closely in line with the space training objectives $v$ provided in $B_T$ space.

### Table 1. IMAV input and output.

| Inputs                                      | Symbols |
|---------------------------------------------|---------|
| Snow liquid water content                   | SLWC    |
| Snow water equivalent                       | SWE     |
| Snow-covered temperature measured in space  | $T_{space}$ |
| Brightness temperature                      | $B_T$   |
| Output                                      | Symbols |
| $B_T$ at 11.05 GHZ, H-polarization          | 11 H    |
| $B_T$ at 11.05 GHZ, V-polarization          | 11 V    |
| $B_T$ at 19.6 GHZ, H-polarization           | 19 H    |
| $B_T$ at 19.6 GHZ, V-polarization           | 19 V    |
| $B_T$ at 38.4 GHZ, H-polarization           | 38 H    |
| $B_T$ at 38.4 GHZ, V-polarization           | 38 V    |

Figure 4. Soil reflectivity in V and H polarization.
Table 2. The output of IMAV for training and estimated target.

| Time period for IMAV training target | 2004–2005 | 2005–2006 | 2006–2007 | 2007–2008 | 2008–2009 | 2009–2010 |
|--------------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| t                                    | o         | o         | o         | o         | o         | o         |
| o                                    | o         | o         | o         | o         | o         | o         |

The optimization is solved for the non-zero Lagrangian multiplier training data sub-set and explained in Equations 12 and 13.

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2} \sum_{k=1}^{n} (\beta_k - \beta_k^*) (\beta_k - \beta_k^*) \phi(y_k) - \phi(y) \\
& + \epsilon \sum_{k=1}^{n} (\beta_k - \beta_k^*) - \sum_{k=1}^{n} (\beta_k - \beta_k^*) \\
& \quad \sum_{k=1}^{n} (\beta_k - \beta_k^*) = 0
\end{align*}
\]

(12)

(13)

(14)

A dual set of lagrangian multipliers is \( \beta_k, \beta_k^* \) and \( \phi(y_k) - \phi(y) \) is a positive constant that determines penalized loss during IMAV training and where \( \epsilon \) is the internal product of the error is specified and \( c \) is a positive constant. In the space used by the kernel function \( \phi(y_k) - \phi(y) \) to generate internal products in the function domain, however, calculation may be carried out in input (LSM) to prevent computational infeasibility problems related to explicitly testing the basis function in a highly dimensional function space.

A radial base kernel function is used to fulfill the statement where individual instances (in space and time) are defined by the Euclidean law and is proportional to the reverse square of the width parameter. Radial base kernel function is explained in equation 15.

\[
S = (y_k, y_t) = \phi(y_k) - \phi(y_t) = \exp\{-\beta||y_k - y_t||^2\}
\]

(15)

\( y_k, y_t \) Represents single instances of \( X \) (in time and space). \(|| \cdot ||\) represents Euclidean norm and \( \beta \) is inversely proportional to square width of parameter.

The overall snow depth equation is the sum of SD values of soil, forest and it is explained in Equation 16.

\[
SD = S_{\text{soil}} \ast SD(\text{soil}) + S_{\text{forest}} \ast SD(\text{forest})
\]

(16)

\[
SD(\text{forest}) = 1.4 + 1.3 \ast S_{\text{snow}} \ast (t_{19h} - t_{37h}) + 2.9 \ast (t_{888} - t_{88h})
\]

(17)

\[
SD(\text{soil}) = 3.7 + 2.2 \ast S_{\text{soil}} \ast (t_{37v} \ast t_{37h}) + 0.02 \ast (t_{18v} - t_{18h})
\]

(18)

where \( S_{\text{forest}} \) is reflect fractions of forest cover, \( S_{\text{soil}} \) is the reflect fractions of soil cover, all these fractions in each of the cells is represented by the IGBP (1 km global ground cover classification); and snow cover fractions, \( t_{19} \) is 18.7 GHz and h-polarization, indicating certain fractions. SWE can be calculated from Equation 19:

\[
\text{Snow Water Equivalent} = SD_{\text{SD}} \ast SD \ast 10
\]

(19)

The goal function used for the IMAV algorithm was specified as MSE. If the output neuron’s target status at time \( t \) is specified as \( V_{s,t} \) in equation 20.

\[
MSE = \frac{1}{2} \sum_{t \in T} \sum_{s \in S} (V_{s,t} - \omega_{s,t})^2
\]

(20)

where the outlet neuron \( o \) is given, \( S \) the total amount of outgoing neurons is given; \( S \) the total number of time steps assessed, \( \forall_{s,t} \) is the value of the training target. \( \omega_{s,t} \) is the estimated value at time \( t \). (Li, 1999)

The output for the training target and the estimated target are given in Table 2. \( T \) is the training target and \( ^o \) is the estimated target.

The output values of IMAV for the training and estimated targets in the year 2004–2010 are clearly explained in Table 2. Here \( t \) is the training set and \( ^o \) is the estimated target.

Results and discussion

The IMAV success evaluation included a number of contrasts between estimated and training targets. (Sun et al., 2006) Contrasts often took place at various locations throughout the northern part of China We find that the RMSE snow depth obtained in the new algorithm is below the RMSE snow depth obtained in the SVM products compared with snow depth reported by the meteorological station and estimated value by the new IMAV and SVM algorithms. Figure 5 summarizes the demonstrated RMSE and deviation for all observed frequency and polarization combinations. (J. Liang et al., 2015) In addition to the full-year statistics, seasonal statistics for December-January-February (DJF) are also given during the accumulation phase, where the snowpack is quite dry as shown in Figure 5(a–c).
Data from different sources have been used for snow modelling. Temperatures and SD have been measured each minute automatically. (Qian et al., 2003) The snow depth for each month is measured as shown in Table 3. The data set contains profile measurements for most of the parameters.

(X. T. Zhang et al., 2008) Snow depth for each month varies as shown in Figure 6. The snow temperature

Table 3. Shows the snow depth for each month varies from Nov to April.

| Snow depth (cm) | Month   |
|-----------------|---------|
| 5               | Nov 01  |
| 20              | Dec 01  |
| 40              | Jan 01  |
| 60              | Feb 01  |
| 80              | Mar 01  |
| 100             | April 01|

Figure 5. (a) Snow depth coverage in December with the distributed frequency ranges. (b) Snow depth coverage in January with the distributed frequency ranges. (c) Snow depth coverage in February with the distributed frequency ranges.

Figure 6. Shows snow depth for each month.
profile observations began at the beginning of the year. Each 20 cm from a soil surface to 100 cm height, electronic sensors calculated the temperature. (T. Liang et al., 2008) Because the interval between SD and measurements of the temperature profile is roughly 500 m, the two locations have a few inch variations between their SDs.

Temperature brightness (Table 4) mainly depends on the snow depth. (Pei et al., 2008) Usually the location had less snow on the weather map than the site on the SD. Because of this, the temperature controls directly buried in the snow became difficult to identify. The fastest sensor reading was used at least 10 cm below the snow line. (Hao, 2004) Statistics on calculation from November to July have been obtained. In November the natural snow came down and melted till last October. The seasons of SD, wet snow and the temperature for snow, soil, and forest are shown in Figure 7.

The temperature for soil is at the same level throughout the year and there will be temperature changes in forest and snow. (X. Wang & Xie, 2009) Results are reported from the month of November to July. The plant temperature was approximately equal to the air temperature calculated in the forest areas.

The Horizontal and Vertical polarization and average statistics RMSE value is calculated for each DJF (December, January, and February), MAM (March, April, May), full year is shown in Table 5 for particular frequency range.

Averaged statistics for each domain in horizontal and vertical polarization and Root Mean Square Error for completion of full year, DJF, MAM is clearly studied. Horizontal and vertical polarization for snow depth and RMSE value is shown in Figure 8.

Dynamic range for averaged statistics for anomaly during the month of DJF, MAM, and FULL year is shown in Table 6. For each horizontal and vertical polarization, there is a slight variation in the dynamic data.

Average values for both horizontal and vertical polarization and values for anomaly over DJF, MAM, FULL year are shown in Figure 9.

The report also provides December–January–February (DJF) seasonal figures during the accumulation phase when snow pack is relatively dry, as well as March–April–May (MAM) as snowpack ripens and is reasonably moist R anomaly as its polarized equivalent during the ablation period. In fact, RMSE is continuing to increase from DJF to MAM for any frequency and polarization, which implies that the IMAV predictive potential is greater if the snowpack is dry than if the snowpack is warm.

Conclusion

This study provides information regarding dual polarization (H and V polarization). In order to chart snow-covered areas across the field of northern China, the difference between the light temperatures at 19 and 37 GHz measured by IMAV was used. For atmospheric effects, the light temperatures have been calibrated using values of snow volume. The results show that IMAV visibility at 19 and 37 GHz is greater when compared with SVM, IMAV has been hybridized and

| Month | Temp for snow | Temp for soil | Temp for forest |
|-------|---------------|---------------|-----------------|
| Nov   | −15           | −10           | −30             |
| Dec   | −10           | −5            | −25             |
| Jan   | −10           | 0             | −20             |
| Feb   | 10            | −15           | −15             |
| Mar   | 15            | −20           | −10             |
| Apr   | −20           | −25           | −5              |
| May   | −25           | −27           | 0               |
| June  | −30           | 5             | 5               |
| July  | −10           | 10            | 10              |

Figure 7. Temperature for snow, soil, forest for each month variations.
the mathematical model has been given out to perform IMAV at 11.05, 19.6, and 38.4 GHz.

The RMSE, H, V polarization and Anomaly for DJF, MAM, and full year of IMAV have been decreased by more than 17% for any of the six frequencies and polarization combinations evaluated, while the anomaly coefficient was raised by more than 50%. The future study will include establishing and applying this research to other times and areas of interest a systematic approach to atmospheric corrections (including elevation impact).

Disclosure statement
No potential conflict of interest was reported by the authors.

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Table 5. Averaged statistics for RMSE during the month of DJF, MAM, FULL year.

| H and V polarization | DJF | MAM | FULL |
|---------------------|-----|-----|------|
| 11                  | 6   | 7   | 6.5  |
| 13                  | 3   | 4   | 4.5  |
| 19                  | 8   | 9   | 8.5  |
| 37                  | 5   | 6   | 5.5  |
| 37                  | 9   | 12  | 10   |
| 37                  | 7   | 11.5| 9.5  |

Table 6. Averaged statistics for anomaly during the month of DJF, MAM, FULL year.

| H and V polarization | DJF | MAM | FULL |
|---------------------|-----|-----|------|
| 11                  | 0.28| 0.32| 0.29 |
| 11                  | 0.48| 0.5 | 0.47 |
| 19                  | 0.33| 0.4 | 0.36 |
| 19                  | 0.49| 0.49| 0.48 |
| 37                  | 0.42| 0.45| 0.44 |
| 37                  | 0.44| 0.46| 0.45 |
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