Monitoring of Time-Series Soil Moisture Based on Advanced DInSAR

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KEY WORDS: Soil Moisture, Time-series Analysis, Advanced DInSAR, Sentinel-1

ABSTRACT:

Understanding soil moisture is essential for earth and environmental sciences especially in geology, hydrology, and meteorology. Remote sensing techniques are widely applied to large-scale monitoring tasks. Among them, DInSAR using multi-temporal spaceborne SAR images is able to derive surface movement up to mm level over an area. One of the factors inducing the movement is variation of soil moisture. Based on this, a semi-empirical approach can be tailored to retrieve the underground water content. However, the derived movement is often contaminated with other irrelevant noise. Besides, a time-series analysis could not be simply implemented without additional fusion and calibration. In this paper, we propose a novel modelling based on advanced DInSAR to solve these problems. The irrelevant noise will be removed as parts of the modelled elements in the DInSAR processing. A forward model on a scene is built by regressing the measured soil moisture on the DInSAR-derived movement series. We tested our approach using Sentinel-1 images in the grasslands of organic soil within State of Brandenburg, Germany. The Pearson correlation coefficients between the measured soil moistures and the DInSAR-derived movements are up to 0.91. The mean square errors of the predicted soil moistures compared with the measurements reach 3.03 % (volumetric water content) at best. Our study shows a promising new concept to develop a global monitoring of soil moisture in the future.

1. INTRODUCTION

Soil moisture is an important factor in geology, hydrology, meteorology, agriculture, disaster analysis, and human activities. For example, it indicates the inflow and outflow of water volume subject to precipitation, snowfall, and frosting, predicts the probability of a forest fire, and controls the effectiveness of arable farming. Measuring the soil moisture via in-situ sensors over a land of a certain size is not cost-effective. Remote sensing has the potential to make such monitoring operational in practice. Many colleagues used spaceborne images in their projects as the signals relevant to moisture across an extensive area can be repeatedly acquired at a short period.

In this study, we focus on spaceborne active SAR to derive soil moisture (Barrett et al., 2009; Das and Paul, 2015; Gabriel et al., 1989; Greifeneder et al., 2019; Huang et al., 2019; Nolan et al., 2003; Paloscia et al., 2013; Tampuu et al., 2020; Zwieback et al., 2017). This all-weather sensor orbits and collects the surface data on Earth around the clock. For example, Sentinel-1 launched in 2014 has been providing the costless images ever since then. The interferometric wide (IW) swath mode acquires a new image at shortest every 6 days, which covers an area of 250 km × 200 km subject to a ground resolution about 5 m × 20 m. We can resort to the commercial satellites like TerraSAR-X if a higher spatiotemporal resolution is demanded. The new SAR constellations like Capella-X and TanDEM-L are scheduled or planned to be launched in the coming future. We believe SAR is an indispensable tool for further development.

There are many different methods and assumptions using SAR images to estimate soil moisture (Barrett et al., 2009; Das and Paul, 2015). In principle, a SAR signal, which is reflected from the ground to the antenna, is subject to many factors such as radar band, backscattering coefficient, polarization, incidence, surface roughness, soil type and texture, vegetation cover, and soil moisture near surface. Many fellows developed theoretical and physical models to retrieve moisture values from SAR signals such as backscattering coefficient and coherence. Actually, these models are often cumbersome and not transferable to different scenes. Part of the reason is that the training data and parameters cannot be accurately quantified or measured all the time. A viable solution is to simplify these models into empirical or semi-empirical versions, which satisfy a certain degree of accuracy. For instance, many studies have validated that the correlation between water contents in soil and backscattering coefficient is nearly positive (Huang et al., 2019; Paloscia et al., 2013). As we know, there is not a golden rule yet in model generalization because most of the parameters must be empirically determined case by case.

The surface movement (mm level) derived by differential interferometric SAR (DInSAR) can be caused by variation of soil moisture (Gabriel et al., 1989; Nolan et al., 2003; Tampuu et al., 2020; Zwieback et al., 2017). This phenomenon results from the change of penetration depth of the SAR signal near the surface, which leads to a pseudo movement. Another reason is credited to swelling and shrinking of (esp. clay- or organic-rich) soil body, which is mainly subject to precipitation and groundwater (self-citation). A semi-empirical approach can then be tailored to obtain soil moisture. However, the soil moisture indices regressed from their movements are often contaminated due to the phase noise. Two main noise sources come from atmospheric and topographic disturbances. Besides, each movement between two image acquisitions is evaluated individually. Hence we cannot simply implement a time-series analysis on soil moisture without additional fusion and calibration. These problems are solved in our new method.

This paper demonstrates a new concept based on a time-series DInSAR - small baseline subset (SBAS) (Berardino et al., 2002; Lanari et al., 2007) for soil moisture monitoring. SBAS computes at once the time-series movement at mm level over an extensive area. The atmospheric and topographic phase noises are

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https://doi.org/10.5194/isprs-annals-V-3-2021-51-2021

suppressed via modelling plus a spatiotemporal filtering. A local forward model of a scene is built by regressing the moisture measurements on the corresponding movement series. Our tests using Sentile-1 images show a promising accuracy level for future development and application.

In the following, we first describe our methodology in Section 2. Section 3 details how to successfully implement our approach in real cases. The test results are then discussed in Section 4. Finally, we conclude our works in Section 5.

2. METHODOLOGY

Our forward model is built via regression to evaluate soil moistures from SBAS-derived movements near ground surface (Figure 1). The soil moisture underground 5 cm is measured as volumetric water content (%) each day at 6 pm by a Decagon 5TM sensor. We estimate the surface movement from Sentinel-1 images via SBAS. The forward model will be refined after first regression. Some inputs, i.e., pairs of movements and moisture readings, are thus removed in second regression if their residual errors exceed a certain tolerance. This step will be iterated until it meets the defined conditions. Finally, a forward model is generated for end use.

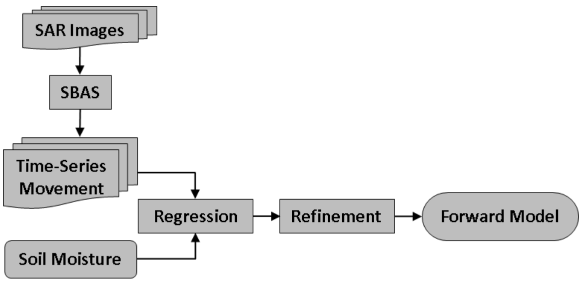


Figure 1. Forward model by regressing soil moisture on time-series movement derived by SBAS.

Figure 2. Decagon 5TM to measure underground soil moisture (https://www.ictinternational.com/products/5tm/decagon-5tm-vwc-temp/)

2.1 SBAS processing

Time-series DInSAR evaluates the surface movement up to submillimeter level over an extensive area. A bunch of SAR images is processed to detect target points of interest. Each target point corresponds to a ground patch of a certain size depending on the image resolution. The signal series within a patch is adequately coherent and so is used to evaluate the local movements of different forms, e.g., cumulative time series or average velocity.

We chose and adapted SBAS (Berardino et al., 2002; Lanari et al., 2007) for the concept and tests of the proposed technique in this study. SBAS suits particularly to detecting target points on natural scenes like bare soil or grassland and results in reasonable movement accuracy. The first step is to generate multi-master interferograms from a SAR image series. These interferogram sets are temporally connected by singular value decomposition (SVD). A pixel is selected as a target point if its ensemble coherence computed from all of the interferograms passes a specified threshold. The target points are then spatially connected by Delaunay triangulation to form a network. Their interferometric phases are unwrapped and then used to interpolate the phases of the remaining points. A transformation is modelled considering the unwrapped interferometric phases and the corresponding movements. The movements are then evaluated via a least square algorithm. The evaluation accuracy is further improved by iteration after removing atmospheric phase screen (APS). For this purpose, the APS-like phases are derived by means of a low-pass spatial filtering and a high-pass temporal filtering.

2.2 Regression to forward model

The forward model is generated by regressing soil moistures on their in-situ surface movements derived by SBAS. We have observed in many cases that the correlation between them is highly positive. We assume the surface movement is mainly caused by the variation of penetration depth of radar wave dependent on the soil moisture close to surface. This short-term phenomenon can be timely perceived following each image acquisition. In contrast, the soil swelling and shrinking is enduring and can be only seen from a long-term movement sequence.

Our regression model is defined empirically as

$$S = \beta + \mathrm{c} \cdot M + \varepsilon \tag{1}$$

where the scalar response S signifies soil moisture expressed as a volumetric water content (%), β means the intercept, c is the regression coefficient of M (soil movement, mm), and ε is assumed to be residual errors subject to M. Here the factor from the soil swelling and shrinking is ignored to avoid overfitting as this effect is usually trivial for a short period.

We feed this model (1) with time series of soil moisture readings and corresponding movements to solve the intercept and coefficient via least square (Teunissen, 2000a, 2000b). Afterwards, the pairs of moisture and movements will be removed in the second regression if their residual errors are greater than a (empirical) sigma threshold. As a result, the forward model is to predict the soil moisture from the SBAS-derived movement.

3. IMPLEMENTATION

Our approach is globally operational as long as the following instructions are fulfilled. The training data must contain both sequences of in-situ soil moistures and surface movements. The moistures are measured successively by a local sensor. The measurements are usually quantified as volumetric water content or permittivity. The sensing depth should be determined by SAR experts and pedologists. General speaking, the shallow moisture changes the penetration depth of a SAR signal; in contrast, the deep water content causes soil swelling and shrinking. In the first case, the sensing depth is usually oriented to at least 5 cm for C-Band radar (Nolan et al., 2003; Nolan and Fatland, 2003).

The variation of penetration depth subject to soil moisture change leads to a pseudo surface deformation, which can be derived by time-series DInSAR like SBAS. The shorter the image

https://doi.org/10.5194/isprs-annals-V-3-2021-51-2021

acquisition interval is, the more timely the moisture change is sensed for an accurate modelling. Currently, the shortest interval is 6 days of Sentinel-1. The interval can be shortened when the coming constellations like Capella-X are fully deployed.

As inputs in regression, the moisture measurements and DInSAR-derived movements must be aligned under a comparable spatiotemporal frame. In this study, the Sentinel-1 images were acquired at around 5 pm, which approaches the sensing time of soil moisture at 6 pm. Three moisture sensors were installed in their respective test areas. Each of these areas is a homogeneous grassland, where the moisture readings indicate the overall scenario. We averaged those point-like movements within each test area to match the moisture readings. By doing so, the residual noise existing in the movements are further suppressed.

For an accurate modelling, the surface movement derived by time-series DInSAR should result from only moisture variation as far as possible. In our case, the atmospheric, topographic, and residual phase noises were modelled and filtered out in SBAS processing. Any changes on ground surface due to vegetation growth, precipitation, snow, etc. will disturb the radar signals. In other words, the affected signal series are not completely coherent over time. Consequently, the surface movement is no longer correlated to the soil moisture, which conflicts our core assumption. Therefore, we excluded the low-coherence phases from the SBAS processing. In addition, we also avoided images, which were acquired during extreme environmental condition or known human activities.

4. EXPERIMENT AND DISCUSSION

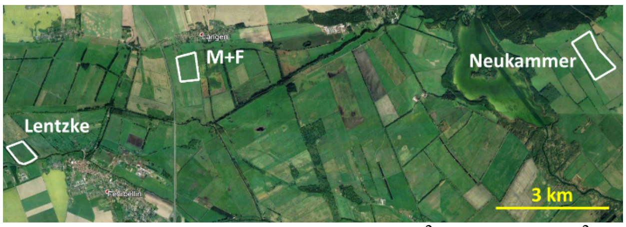


Figure 3. Test grasslands Lentzke (0.2 km^2), M+F (0.3 km^2), and Neukammer (1.0 km^2) in State of Brandenburg, Germany.

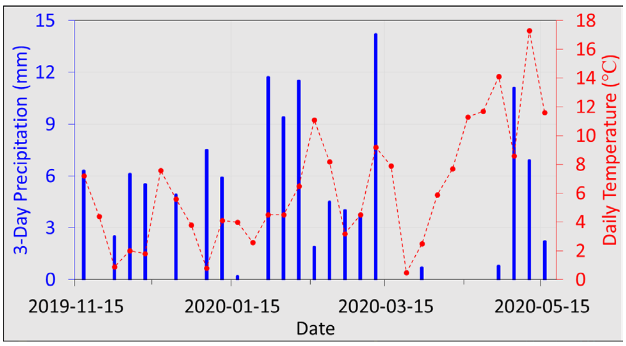


Figure 4. Measurement of precipitation (mm) and temperature (°C) around test grasslands (Figure 3) during 6 months from weather stations of Germany's National Meteorological Service. Precipitation is cumulated every 3 days. Temperature is daily averaged. Sample dates correspond to when our Sentinel-1 images were acquired.

Three test grasslands named Lentzke, M+F, and Neukammer are located around 50 km northwest of Berlin (Figure 3). Figure 4 shows the surrounding precipitation and temperature measurements. Their sample dates correspond to when our Sentinel-1 images were acquired (Figure 5). Each test area is characterized by homogeneous vegetation cover, soil type, and water content. The sensors were installed properly by Anonymity to measure the soil moisture each day every 6 hours from mid-November 2019 to mid-May 2020 (Figure 6). Here we used only the data measured at 6 pm close to the acquisition times of the Sentinel-1 images. Overall, the moistures before mid-March 2020 changed rather insignificantly as the rainfall and temperature varied randomly. Afterwards, the drought began for nearly two months; meanwhile, the temperature kept raising. Consequently, the soil moistures dropped straight.

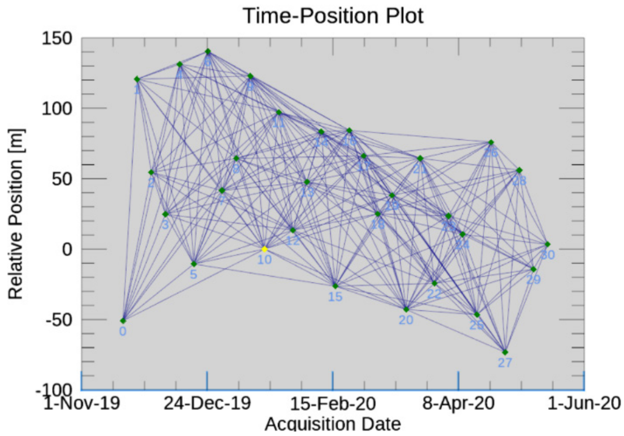
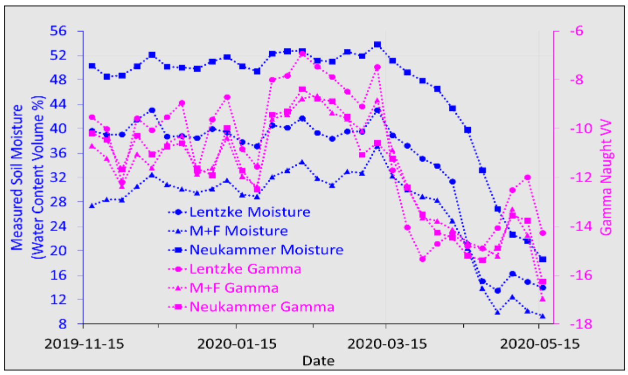
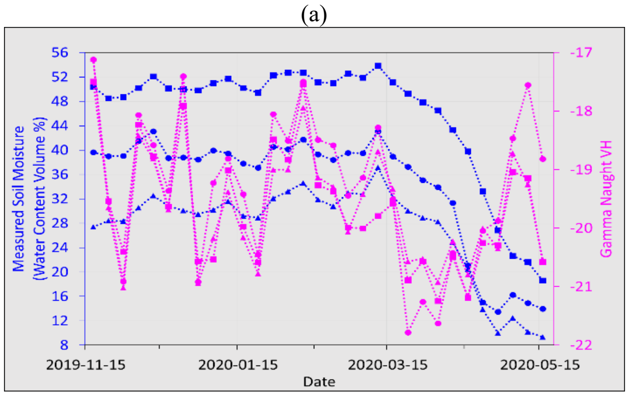


Figure 5. Normal and temporal baselines of connected image pairs in SBAS processing.



(a)



(b)

Figure 6. Comparison of soil moisture and Gamma Naught of (a) VV- and (b) VH-polarized SAR signals at test grasslands (Figure 3).

We involved 31 Sentinel-1 images in our analysis. These images were VV/VH-polarized, taken under ascending Interferometric Wide (IW) swath mode from mid-November 2019 to mid-May 2020, and resampled to ground distance of 30 m × 30 m. The VV-and VH-polarized complex signals were calibrated into Gamma naught values, whose correlation to soil moisture is assumed to approximate linear or at least partly (Huang et al., 2019; Paloscia et al., 2013). Gamma naught is defined as the intensity of the complex signal reflected from ground. It can be interpreted as the calibrated radar brightness of an image pixel, which is independent from the local incidence. An empirical or semi-empirical model can hence be generated for further monitoring. Our comparison in Figure 6 shows that the VV cases more conform to this assumption than the VH cases. The former's Pearson correlation coefficients (PCC) are 0.67, 0.84, and 0.76 for the three test sites; the latter's 0.77, 0.78, and 0.22 (Table 1). In general, the correlation is not stable enough for a repeatable modelling. This conclusion is also found in many other studies.

Grassland	PCC_SVV	PCC_SVH	PCC_SM	MAE_SS (%)
Lentzke	0.67	0.77	0.91	3.15
M+F	0.84	0.78	0.88	3.03
Neukammer	0.76	0.22	0.82	4.47

Table 1. Comparison between measurement and evaluation. PCC_SVV, *_SVH, and *_SM: PCC of measured soil moisture to VV-polarized Gamma Naught, VH-polarized Gamma Naught, and SBAS-movement. MAE_SS, mean absolute error between measured and predicted soil moistures (via respective forward models).

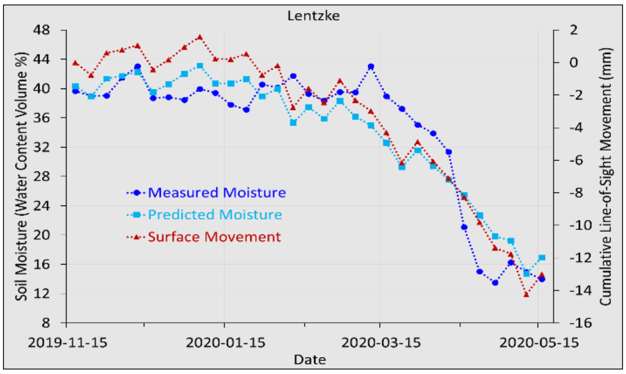


Figure 7. Comparison of soil moisture and SBAS-derived movement at Lentzke (Figure 3). Movement: negative and positive, away and towards Sentinel-1 antenna. Sample dates correspond to Sentinel-1 acquisitions.

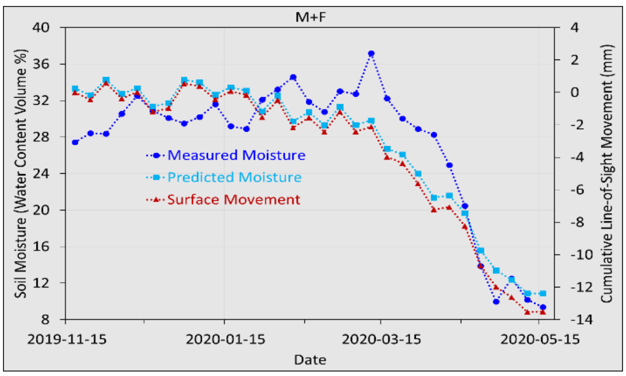


Figure 8. Comparison of soil moisture and SBAS-derived movement at M+F (Figure 3).

Our approach implemented SBAS processing to compute the surface movement of the test areas. Here only the VV-polarized Sentinel-1 images were used (Figure 5). The resultant cumulative movement series along line of sight are averaged within each test grassland (Figure 7, Figure 8, and Figure 9). Their PCCs to the measured soil moistures are 0.91, 0.88, and 0.82, which are generally more correlated than those subject to the Gamma naught values (Table 1). These three PCCs are sufficiently high to validate the core assumption in our modelling. For the lowest PCC 0.82, the decorrelation is mainly subject to the dissimilarity during the middle period (Figure 9). The pedologists inferred that the moistures back then were overmeasured as the infiltrated water accumulated on the sensing elements.

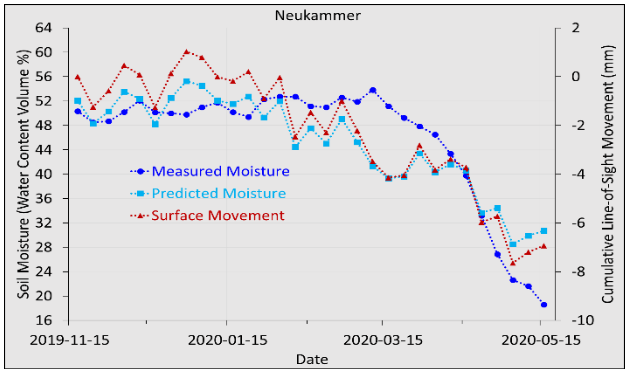


Figure 9. Comparison of soil moisture and SBAS-derived movement at Neukammer (Figure 3).

We predicted the soil moistures at the three test areas from their forward models (Figure 7, Figure 8, and Figure 9). Their mean absolute errors to the ground truth data are 3.15, 3.03, and 4.47 % during the measurement period of 6 months (Table 1). The last accuracy is the worst as expected because of overmeasured reading. In fact, our approach rather than the in-situ sensor might catch the actual moisture condition. According to the accuracy, we believe our approach is promising for a time-series monitoring.

Last but not least, we conducted a blind test to check the modelling transferability in case a local measurement is unavailable. The forward model of Lentzke was then applied to evaluate the soil moistures in the test sites M+F and Neukammer. These three areas possess similar vegetation and soil type above shallow layer. This consistency is prerequisite for model transfer. Here we added an offset into the model to balance the difference of the initial moistures among the areas. As a result, the PCCs are 0.88 and 0.82 and the mean absolute errors are 3.19 and 4.72 % (Table 2). The mean absolute errors are increased only up to 0.25 % compared with the tests using their own models (Table 1). We hence regard the accuracy subject to a transferred model is comparable to its own model given well controlled conditions. Even if an offset lacks to obtain absolute soil moistures, the precision according to the PCCs over 0.8 suffices for evaluating relative moisture change.

Grassland	PCC	MAE (%)
M+F	0.88	3.19
Neukammer	0.82	4.72

Table 2. Comparison between measured and predicted soil moistures (via forward model computed from Lentzke data). MAE, mean absolute error.

5. CONCLUSIONS

Our novel approach is able to evaluate the time-series soil moisture of a certain region from multi-temporal spaceborne

SAR images. We have tested it using Sentinel-1 images in three grasslands of organic soil Lentzke, M+F, and Neukammer within State of Brandenburg, Germany for a 6-month period. The PCCs between the measured soil moistures and the DInSAR-derived movements are 0.91, 0.88, and 0.82 (average 0.87). Such a high correlation satisfies the prerequisite to our forward modelling.
The soil moistures predicted from the forward models were compared with the measurements. The mean absolute errors (volumetric water content) are 3.15, 3.03, and 4.47 % (average 3.55%). The absolute accuracy seems quite impressive considering that the actual moistures dropped around 30 % in 6 months. We also applied the Lentzke's forward model to M+F and Neukammer sites to check the transferability. The mean absolute errors are raised merely up to 0.25 %. Overall, we believe our modelling is ready for local end use at least for those sites similar to ours, i.e., low vegetation coverage plus organic soils. We will adapt our approach for different site conditions, e.g., dense vegetation coverage or inorganic soil body. Under these conditions the soil moisture might not be caught in a way we assumed. For instance, if an area is moving up and down due to groundwater use, this physical movement must be excluded from the pseudo movement caused by moisture variation. To do so, the auxiliary knowledge or data such as in-situ GNSS measurement are prerequisite.

The proposed technique can be integrated with other platforms and systems for a global monitoring mission. The necessary input data for modelling are SAR images and in-situ moisture measurements. The Sentinel-1 images has proven workable in our study, which are costless and cover nearly the global land. In case a local measurement is not available for modelling, we have proven that the relative moisture change can be computed based on advanced DInSAR. Another solution is to train the forward model at an alike region, which is reachable to collect the measured data. We can check the homogeneity between different areas by using remote sensing to determine if a model transfer is feasible.

In the coming future, we first plan to extend the current 6-month test period to at least one year covering four seasons. We will analyze the influences of natural factors on our modelling in more detail, e.g., temperature, rainfall, vegetation growth, etc. Secondly, we will repeat our tests under different site conditions. The descending Sentinel-1 images and other SAR sources of X-Band and L-Band would be involved for further exploration. The feasibility, portability, and robustness of our approach will be further validated. In addition, the vertical and horizontal surface movements will be derived from decomposition of both ascending and descending DInSAR results. We will explore their relation to our modelling. Last but not least, we are discussing with Capella Space about creating a pilot project. The new coming Capella-X constellation would be used to monitor the soil moisture at a region of interest every 2 to 3 days based on our approach.

ACKNOWLEDGEMENT

We appreciate the free accesses to the data used in this study. The Sentinel-1 images are provided by Copernicus - European Union's Earth Observation Programme. The precipitation and temperature were downloaded from Deutscher Wetterdienst. We also want to thank our partners within the BEWAMO Project (funded by the German Federal Ministry of Food and Agriculture under Grant no. 281B301416.) for the provision of measurement data and technical discussion. Among them, Mr. Andreas Herrmann at Institute of Agricultural and Horticultural Sciences, Humboldt-Universität zu Berlin contributed his great support to the soil moisture measurement.

REFERENCES

Barrett, B.W., Dwyer, E., Whelan, P., 2009. Soil moisture retrieval from active spaceborne microwave observations: An evaluation of current techniques. Remote Sens., 1(3), 210–242.

Berardino, P., Fornaro, G., Lanari, R., Sansosti, E., 2002. A New Algorithm for Surface Deformation Monitoring Based on Small Baseline Differential SAR Interferograms. IEEE Trans. Geosci. Remote Sens., 40(11), 2375–2383.

Das, K., Paul, P.K., 2015. Present status of soil moisture estimation by microwave remote sensing. Cogent Geosci., 1(1).

Gabriel, A.K., Goldstein, R.M., Zebker, H.A., 1989. Mapping small elevation changes over large areas: differential radar interferometry. J. Geophys. Res., 94(B7), 9183–9191.

Greifeneder, F., Khamala, E., Sendabo, D., Wagner, W., Zebisch, M., Farah, H., Notarnicola, C., 2019. Detection of soil moisture anomalies based on Sentinel-1. Phys. Chem. Earth, 112, 75–82.

Huang, S., Ding, J., Zou, J., Liu, B., Zhang, J., Chen, W., 2019. Soil moisture retrival based on sentinel-1 imagery under sparse vegetation coverage. Sensors, 19(3).

Lanari, R., Casu, F., Manzo, M., Zeni, G., Berardino, P., Manunta, M., Pepe, A., 2007. An Overview of The Small Baseline Subset Algorithm: A DInSAR Technique for Surface Deformation Analysis. Pure Appl. Geophys., 164(4), 637–661.

Nolan, M., Fatland, D.R., 2003. Penetration depth as a DInSAR observable and proxy for soil moisture. IEEE Trans. Geosci. Remote Sens., 41(3), 532–537.

Nolan, M., Fatland, D.R., Hinzman, L., 2003. DInSAR measurement of soil moisture. IEEE Trans. Geosci. Remote Sens., 41(12 PART I), 2802–2813.

Paloscia, S., Pettinato, S., Santi, E., Notarnicola, C., Pasolli, L., Reppucci, A., 2013. Soil moisture mapping using Sentinel-1 images: Algorithm and preliminary validation. Remote Sens. Environ., 134, 234–248.

Tampuu, T., Praks, J., Uiboupin, R., Kull, A., 2020. Long term interferometric temporal coherence and DInSAR phase in Northern Peatlands. Remote Sens., 12(10), 7–9.

Teunissen, P.J.G., 2000a. Adjustment Theory: An Introduction. VSSD, Delft, The Netherlands.

Teunissen, P.J.G., 2000b. Testing Theory: An Introduction. VSSD, Delft, The Netherlands.

Zwieback, S., Hensley, S., Hajnsek, I., 2017. Soil Moisture Estimation Using Differential Radar Interferometry: Toward Separating Soil Moisture and Displacements. IEEE Trans. Geosci. Remote Sens., 55(9), 5069–5083.