ESTIMATION OF LOCAL-SCALE SOIL MOISTURE BY THE INTEGRATION OF SENTINEL-1 SAR AND SENTINEL-2 MSI IMAGES WITH DEEP NEURAL NETWORK

Soo-Jin Lee (1), Yang-Won Lee (1)

[1] Pukyong National University, 45, Yongso-ro, Nam-Gu. Busan, 48513, Korea
Email: love2002911@gmail.com; modconfi@pknu.ac.kr

KEY WORDS: Sentinel-1, Sentinel-2, DNN, Soil moisture

ABSTRACT: Soil moisture is a major factor affecting climate, carbon cycle, hydrological mechanisms through controlling latent heat flux, rain-runoff and so on. In this study, soil moisture modeling was performed using deep neural network (DNN) technique, Sentinel-1 synthetic-aperture radar (SAR) image and Sentinel-2 multispectral instrument (MSI) image provided by European Space Agency (ESA) for high resolution soil moisture estimation and accuracy improvement. The accuracy of estimated the soil moisture was RMSE of 5.796% and correlation coefficient of 0.835. In other words, the accuracy of the soil moisture calculation can be improved through high resolution images and DNN model optimization.

1. Introduction

Soil moisture is a major factor affecting climate, carbon cycle, hydrological mechanisms through controlling latent heat flux, rain-runoff and so on. The satellite-based soil water data are ESA's Soil Moisture and Ocean Salinity (SMOS) and NASA's soil moisture active passive (SMAP) data.

Both SMAP and SMOS provide global soil moisture data calculated by using the brightness temperature measured from a passive L-band (1.4 GHz) microwave radiometer. The microwave method has the advantage of being able to pass through clouds, fog, dust, and rain because of its non-sensitive feature to the atmospheric scattering. However, it is difficult to grasp the distribution of soil moisture at the regional level by using passive microwave - based soil moisture data in present. Because they have low spatial resolution (SMOS: 30-50 km, SMAP: 9-36 km).

The purpose of this study is estimating the soil moisture content by using deep neural network (DNN) technique, Sentinel-1 synthetic-aperture radar (SAR) image, and Sentinel-2 multispectral instrument (MSI) image provided by European Space Agency (ESA) to provide the distribution of soil moisture at the local level and improve the accuracy.

2. METHODOLOGY

2.1 Study area and test data

The study area is cropland in Saskatoon and Manitoba, Canada. The study period is from May to September, 2016 to 2018. Soil moisture data were obtained from Canadian "RISMA" (Real-Time In-Situ Soil Monitoring for Agriculture) network data. There are 4 stations in Saskatoon and 12 in Manitoba(Fig. 1). The main crops of farmland where the stations are located are barley, canola, corn, grassland, pasture, soybeans, and spring wheat. Some stations (MB5, MB6, MB8, and MB10) where soil texture is clay and heavy clay are excluded. Because the clay and heavy clay with low infiltration rate unlike other soil textures are more likely to cause run-off than infiltration. Therefore, it is likely to present water on the ground after irrigation or precipitation. The water on the ground can affect as noise in backscattering signals for soil moisture (Hobbs et al., 1998).

ESA Sentinel-1 is a C-band (5.404 GHz) SAR and supports 10 m high-resolution polarimetric microwave imaging. Currently, the data are provided about every 6 days in Europe and every 12 days in other regions. HH, HV polarized images in polar regions and VV, VH polarized images in the other regions are provided. VV polarization backscatter data and the angle of incidence data were used for the DNN modeling. Because VV polarization backscatter is more sensitive to soil moisture than VH polarization (Lee et al, 2017).

Sentinel-2 is a multi-spectral satellite with 13 bands in the visible, near infrared, and short-wave infrared part of the spectrum. The data are provided about every 5 days in most areas and 10 days in some areas. The spatial resolution is 10, 20, and 60m, and different for each band. It is used to calculate normalized difference vegetation index (NDVI) which reflects the vegetation characteristics of the ground.

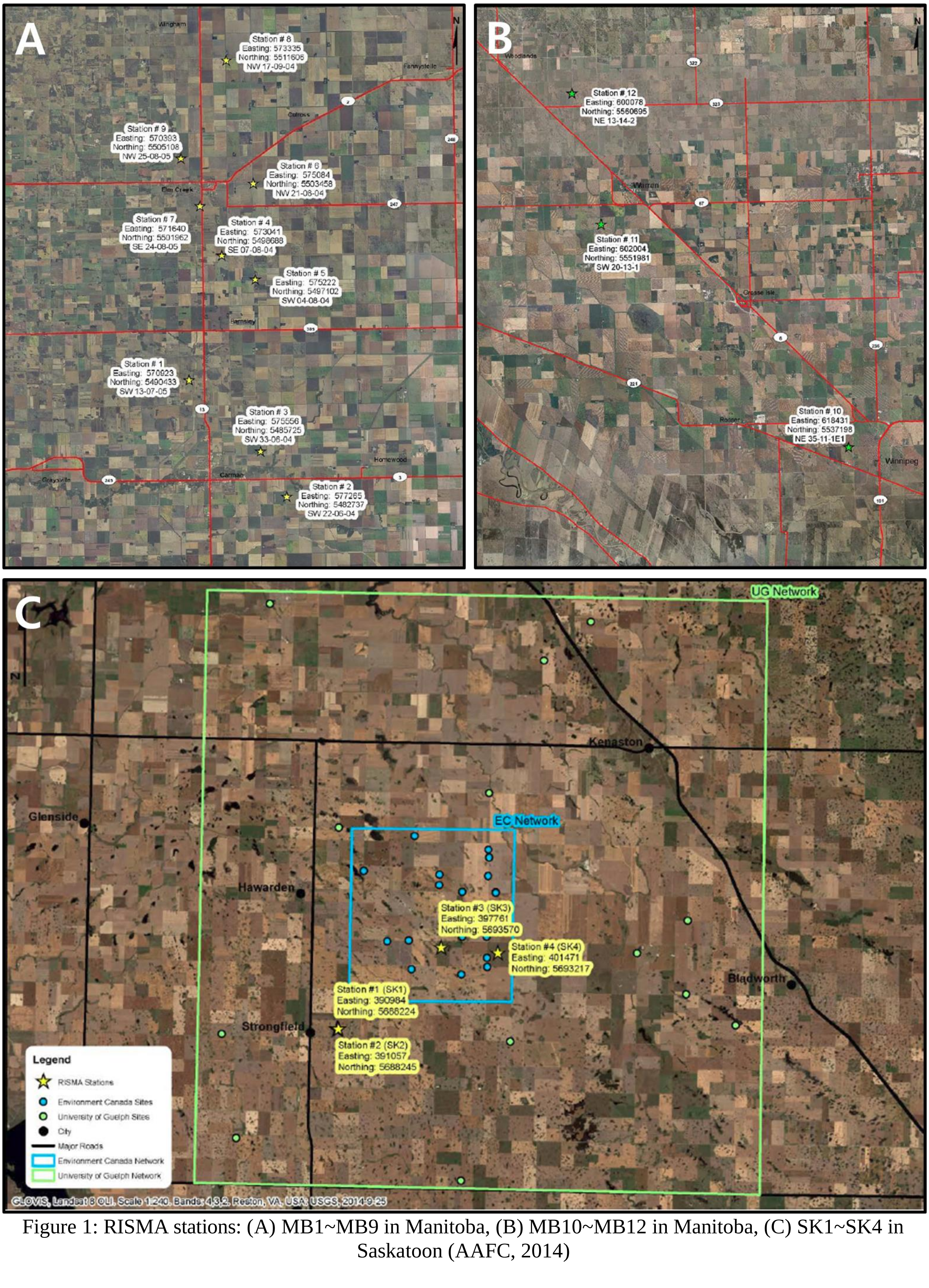

Figure 1: RISMA stations: (A) MB1~MB9 in Manitoba, (B) MB10~MB12 in Manitoba, (C) SK1~SK4 in Saskatoon (AAFC, 2014)

2.2 Deep Neural Network

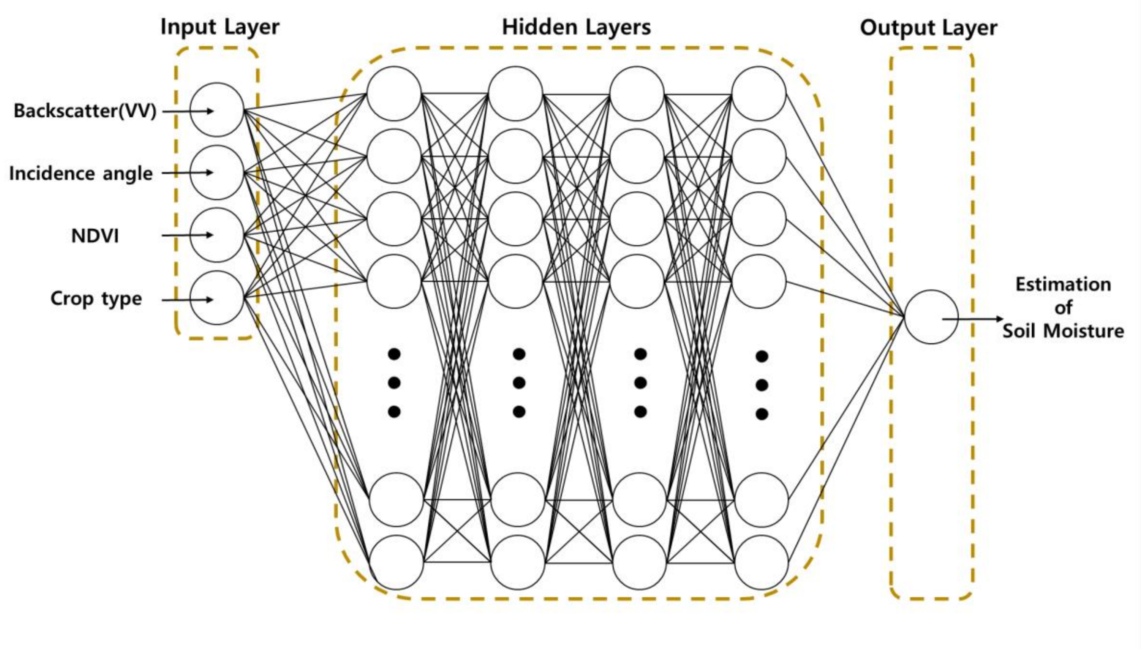

Figure 2: DNN structure

Table 1: Used hyper-parameters

Hyper-parameter	Setting
Hidden layer	[200, 200, 200, 200]
Loss function	Mean Squared error (MSE)
Optimizer	Adaptive gradient (AdaGrad)
Activation Function	Rectified linear unit (ReLU)
Epoch	30
Batch Size	1
Dropout ratio	0

DNN is the method of predicting through training in deep neural networks with a number of hidden layers. This can overcome the local minima problem in neural networks and overfitting problems in machine learning through backpropagation and hyperparameter optimization of the model (Shrestha and Mahmood, 2019). The DNN model in this study was tested using the Google TensorFlow library. Hyper-parameters that affect DNN performance were optimized based on the low value of the loss function (MSE, mean squared error) (Table 1). The DNN model consists of input layer, four hidden layers, and output layer (Fig. 2). The input data consists of VV-backscatter, incidence angle, NDVI, and crop type (Fig. 2). The spatial resolution of each input data is resampled to 50m to reduce noise of VV. The hidden layer is set up with 4 layers of 200 nodes. The performance of the DNN model was evaluated through 10-Fold Cross Validation.

3. RESULTS

In order to determine the accuracy of the soil moisture estimated through DNN modeling, Mean Bias Error (MAB), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R (correlation coefficient) were calculated. Table 2 shows the average values of MBE, MAE, RMSE, and R for 10 folds. MAE and RMSE were 4.460% and 5.796%, respectively, and MBE was 0.098%, which was almost close to zero. The correlation coefficient was 0.835, indicating a high positive correlation. The estimated and observed soil moisture showed distribution close to one-to-one line (Fig. 3)

Table 2: Validation accuracy for estimated soil moisture

MBE	MAE	RMSE	Cor.
0.098	4.460	5.796	0.835

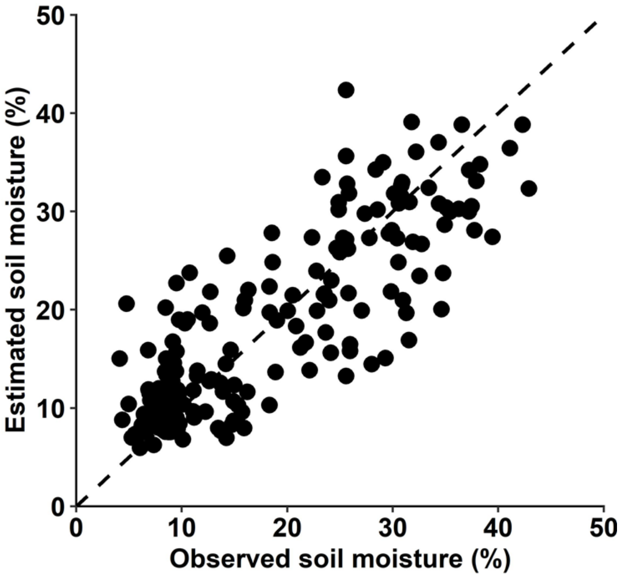

Figure 3: Scatter plot between estimated soil moisture and observed soil moisture

4. CONCLUSION

In this study, we developed the DNN model for soil moisture through high resolution images (sentinel-1, 2) and the optimization of the DNN model. The accuracy of the soil moisture was MAE 4.46% and RMSE 5.796%, and the correlation coefficient was 0.835. Through this analysis, we could identify the potential for improving the accuracy of soil moisture through the optimization process of the model and providing the local soil moisture information.

References

Agriculture and Agri-Food Canada (AAFC), 2014. Agriculture and Agri-Food Canada’s Real-Time In-Situ Soil Monitoring for Agriculture (RISMA) Network Metadata, Retrieved December, 2014, from https://agriculture.canada.ca/SoilMonitoringStations/index-en.html

Hobbs, S., Ang, W., and Seynat, C. 1998. Wind and rain effects on SAR backscatter from crops, European Space Agency-Publications-ESA SP, 441, 185-190.

Lee, S., Hong, S., Cho, J., and Lee, Y., 2017. Experimental Retrieval of Soil Moisture for Cropland in South Korea Using Sentinel-1 SAR Data, The Korean Society of Remote Sensing, 33 (6), pp. 947-960.

Shrestha, A., and Mahmood, A., 2019. Review of Deep Learning Algorithms and Architectures. IEEE Access, 7, 53040-53065.