CHAPTER 6

ARTIFICIAL NEURAL NETWORK BASED SOIL MOISTURE ESTIMATION USING MICROWAVE REMOTE SENSING

6.1 INTRODUCTION

Soil moisture is a critical parameter of the water cycle over land surface. Increase in soil moisture beyond the saturation level is a pointer towards occurrence of flood in a particular area. Hence, remote sensing of soil moisture is of utmost importance in studies related to flood prediction and monitoring [56]. It is one of the most closely associated aspect of flood occurrence. The use of microwave remote sensing in soil moisture studies has been elaborately explained in Chapter-1. However, in places having large open water bodies, the conventional remote sensing algorithms for soil moisture measurement do not give correct values of soil moisture [57-59]. Hence, there is a need for development of a new method for soil moisture measurement in such places using microwave remote sensing. This chapter presents such a soil moisture measurement method, developed using passive microwave remote sensing, for accurate measurement of soil moisture in places having large water bodies.

The sections of the chapter are organized as the following. Section 6.2 presents the theoretical background pertaining to the present work. Section 6.3 gives an idea regarding the equipments, software and data used for the work. Section 6.4 shows the study area selected for testing and validation of the proposed method. Section 6.5 is about the experiments done. The experimental results and their validation methods are explained in Section 6.6.

6.2 THEORETICAL BACKGROUND

Soil moisture can be derived from passive microwave remote sensed brightness temperature values by using the methodology as described in this section. The methodology developed is based on Artificial Neural Network (ANN). Two Methodologies for deriving Soil Moisture from Passive Microwave Remote sensors have been experimented, where ANNs are used.

The concepts of dependency of brightness temperature on dielectric constant and the use of polarization index in soil moisture measurement have been discussed in previous chapters. Here the concept of ANN used for estimation of parameters is explained in brief.

An Artificial Neural Network (ANN) is a computing system that is inspired by the way biological nervous systems process information. It is composed of a large number of highly interconnected processing elements called neurons, working together to solve specific problems. ANNs, like human beings, learn by example. An ANN is configured for a specific application, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well [71].

An artificial neuron with its input, output and teaching-learning mechanism is shown in Figure 6.1. The typical layers of an ANN are shown in Figure 6.2.

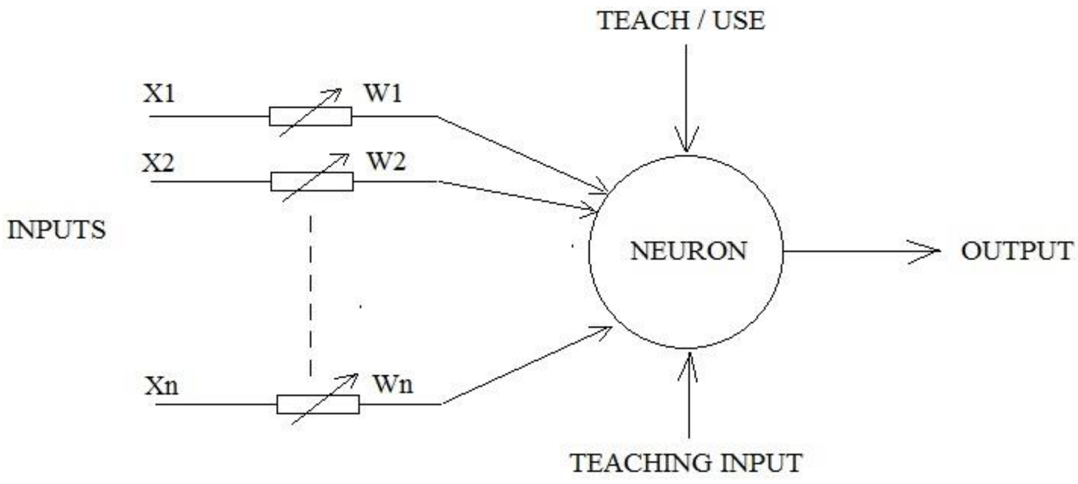

Figure 6.1: An Artificial Neuron [71]

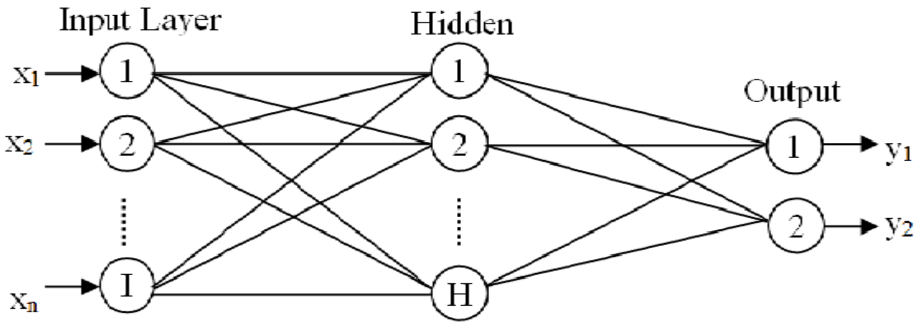

Figure 6.2: Typical layers of an ANN

In the neuron model of the figure the inputs are 'weighted'. The weight of an input is typically a number, which when multiplied with the input, gives the weighted input. These weighted inputs are then added together. If these weighted inputs exceed a pre-set threshold value, the neuron fires. In any other case the neuron does not fire.

In mathematical terms, the neuron fires if and only if;

$$X1W1 + X2W2 + X3W3 + ... > T \tag{6.1}$$

Various algorithms exist that cause the neuron to 'adapt'. The most popular one is the error back-propagation algorithm. In the present work, this algorithm is used.

6.3 EQUIPMENTS, SOFTWARES AND DATA USED

Following are the equipments and data used for the study.

(a) A PC with ‘Beam VISAT’ software for extracting brightness temperature data from the remote sensing images is used.
(b) ‘MATLAB’ software with ‘Neural Network toolbox’ is used for configuring the ANNs.
(c) Brightness temperature images from AMSR 2 sensor on board GCOM-W1 satellite, in all the frequencies and polarizations are used.

6.4 STUDY AREA

The study areas from where the soil samples are collected are in the state of Meghalaya in India. The places with their coordinates are- Mawlai (latitude 25.5°N and longitude 91.8°E), Mawlynrei (25.5°N, 91.9°E), Raliang (25.4°N, 92.3°E) and Jowai (25.4°N, 92.2°E). Soil samples are collected on different dates ranging from October 2015 to April 2016.

The map of the whole state of Meghalaya is shown in the Figure 6.3. In the north side, the boundary is mostly shared with Assam. The south side boundary is with Bangladesh. The study locations are from the following two districts.

(a) East Khasi Hills district: Mawlai and Malynrei.
(b) Jaintia Hills district: Raliang and Jowai.

Figure 6.3: The districts and the boundaries of the state of Meghalaya in India
[Source: *https://bhuvan.nrsc.gov.in/bhuvan_links.php*]

6.5 EXPERIMENTS DONE

There are two neural network based soil moisture estimation methodologies designed and tested for their accuracy values. The details of the two methodologies are discussed in the following.

For the first methodology (Methodology-1), the first neural network, named as *ANN 1*, is trained using all 14 brightness temperature values (both horizontal and vertical polarization values) at all the 7 frequencies (6, 7, 10, 18, 22, 36 and 89 GHz) of AMSR-2 as input and actual soil moisture values measured by using gravimetric method as the target.

For the second methodology (Methodology-2), the second neural network, named as *ANN 2*, is trained using brightness temperature values at 6 GHz for both Horizontal and Vertical polarizations, as well as Polarization Index (*PI*) computed at 10 GHz as inputs (3 inputs), and soil moisture measured using gravimetric method as the target. The selection of the frequencies such as 6 GHz brightness temperature and 10 GHz polarization index are done after a preliminary study using all available frequencies. In the study the trial results show more accuracy while using 6 GHz for brightness temperature and 10 GHz polarization index, as compared to all other frequencies and their different combinations.

For the first ANN, the number of input nodes is 14, the number of hidden layers is 3 and the number of output nodes is 1. For the second ANN, the number of input nodes is 3, the number of hidden layers is also 3 and the number of output nodes is 1. The learning rate was kept at 0.001 with acceptable mean square error level kept as 10^{-3}.

Comparison between the two Methodologies is done in terms of their accuracy. Figure 6.4 shows the comparison done between the two methodologies used for determining soil moisture from passive microwave data.

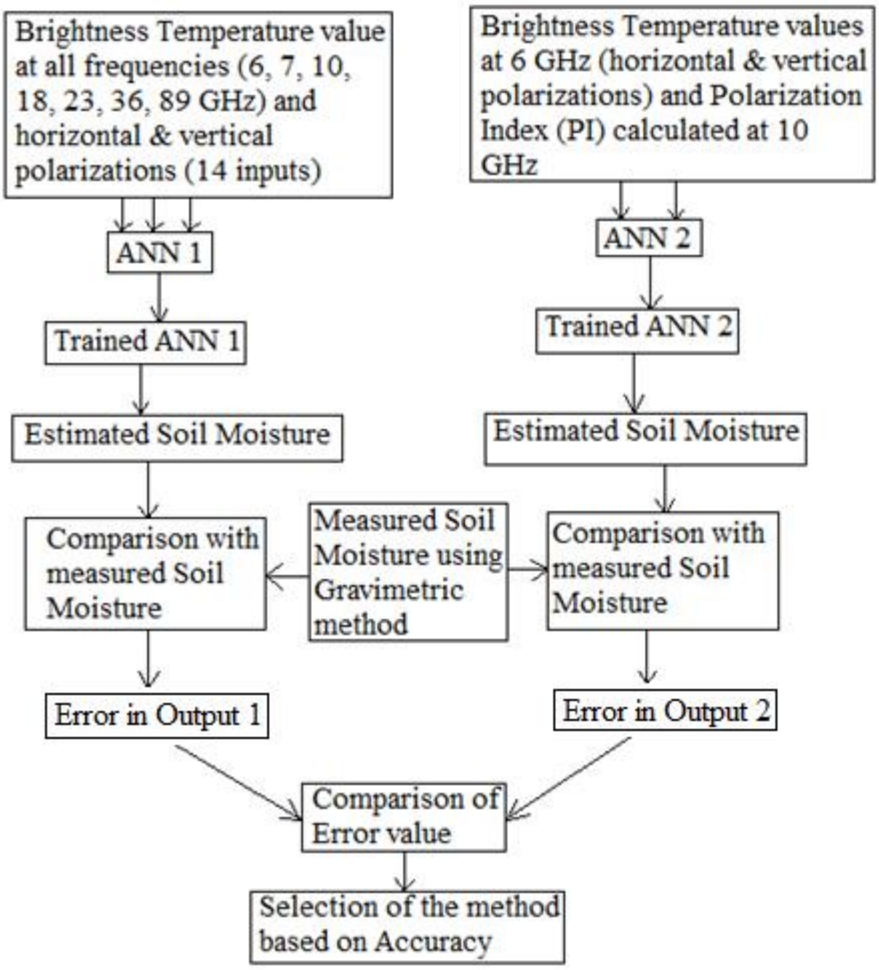

Figure 6.4: Methodologies of ANN based soil moisture estimation using brightness temperature

The soil samples are collected during the morning hours from all the places of study, so that the measured soil moisture can be compared with the remote sensed brightness temperatures measured by the satellite passing over the area during the same time. The soil samples collected from the sites on a particular day are kept in zip locked plastic bags as shown in Figure 6.5, so that the moisture content in the sample remains intact, till the weighing is done.

Figure 6.5: Soil samples collected in zip locked bags from different places

For training and configuring both *ANN 1* and *ANN 2*, the different types of transfer functions and training algorithms used are listed in Tables 6.1 and 6.2 respectively.

Table 6.1: List of transfer functions used in training and configuring the ANNs

Sl. No.	Transfer function	Abbreviated function name
1	Symmetric sigmoid transfer function	*Tansig*
2	Linear transfer function	*Purelin*
3	Logarithmic sigmoid transfer function	*Logsig*
4	Elliot symmetric sigmoid transfer function	*Elliotsig*

The transfer functions with their mathematical relations are shown in the following.

Symmetric sigmoid transfer function: $S(x) = \frac{1}{1+e^{-x}} = \frac{e^{x}}{e^{x}+1}$

Linear transfer function: $S(x) = ax$

Logarithmic sigmoid transfer function: $S(x) = ln\left(\frac{1}{1+e^{-x}}\right)$

Elliot symmetric sigmoid transfer function: $S(x) = \frac{x}{1+|x|}$

Table 6.2: List of training algorithms used in training and configuring the ANNs

Sl. No.	*Training algorithm*	*Abbreviated algorithm name*
1	Gradient descent with adaptive learning rate	*Traingda*
2	Levenberg-Marquardt optimization	*Trainlm*
3	Resilient backpropagation	*Trainrp*

The training algorithms used are briefly described in the following.

(1) Gradient descent with adaptive learning rate (*traingda*) can train any network as long as its weight, net input, and transfer functions have derivative functions.

$$dX = lr*dperf/dX$$

At each epoch, if performance decreases toward the goal, then the learning rate is increased by the factor *lr_inc*. If performance increases by more than the factor *max_perf_inc*, the learning rate is adjusted by the factor *lr_dec* and the change that increased the performance is not made.

(2) Levenberg-Marquardt optimization (*trainlm*) supports training with validation and test vectors if the network's *NET.divideFcn* property is set to a data division function. Validation vectors are used to stop training early if the network performance on the validation vectors fails to improve or remains the same for *max_fail* epochs in a row. Test vectors are used as a further check that the network is generalizing well, but do not have any effect on training. *trainlm* can train any network as long as its weight, net input, and transfer functions have derivative functions.

(3) Resilient backpropagation (*trainrp*) can train any network as long as its weight, net input, and transfer functions have derivative functions.

Backpropagation is used to calculate derivatives of performance with respect to the weight and bias variables X. Each variable is adjusted according to the following:

*dX = deltaX.*sign(gX);*

where, the elements of *deltaX* are all initialized to *delta0*, and *gX* is the gradient. At each iteration the elements of *deltaX* are modified. If an element of *gX* changes sign from one iteration to the next, then the corresponding element of *deltaX* is decreased by *delta_dec*. If an element of *gX* maintains the same sign from one iteration to the next, then the corresponding element of *deltaX* is increased by *delta_inc*.

ANN1 and *ANN2* are trained, tested and validated using different combinations of the transfer functions and the training algorithms. After training and testing the ANNs are used to estimate the soil moisture values, with the brightness temperature values as inputs. The soil moisture values estimated by both the ANNs are then compared with the actual measured soil moisture values. Finally the better one is selected based on the experimental results.

6.6 EXPERIMENTAL RESULTS AND VALIDATION OF RESULTS

Estimated soil moisture values with percentage errors for both *ANN 1* and *ANN 2* using different learning algorithms and transfer functions as shown tables 6.1 and 6.2 are computed. The actual soil moisture values are determined for samples collected physically from different sites (as mentioned in section 6.4) by doing laboratory measurement using gravimetric method. Error is thus found in estimated values in comparison with the actual measured soil moisture values. The formula used for error computation is shown in the following.

$$Percentage\ error = \frac{ANN\ estimated\ soil\ moisture - Laboratory\ measured\ soil\ moisture}{Laboratory\ measured\ soil\ moisture} \times 100$$

The ANN configurations having least values of errors in estimating soil moisture are considered suitable to use. Thus the ANN configuration having good accuracy for both the methodologies and for all the four places is selected for the purpose of estimating soil moisture from the brightness temperature values. Tables 6.3 to 6.6 present the most accurate configurations of ANNs determined from the above mentioned experiments done over a period of two years during 2015 - 2016.

Table 6.3: Accuracy of *ANN 1* in estimating soil moisture for '*Gradient descent with adaptive learning rate*' algorithm and '*Elliot symmetric sigmoid*' transfer function

Places	Mawlynrei	Mawlai	Jowai	Raliang
Estimated soil moisture by *ANN1* in percentage	34.4	27.4	32.6	31.6
Measured soil moisture in percentage	38	26	35	30
Percentage Error	-9.5	5.4	-6.9	5.3

Table 6.4: Accuracy of *ANN 1* in estimating soil moisture for '*Resilient backpropagation*' algorithm and '*Symmetric sigmoid transfer function*' transfer function

Places	Mawlynrei	Mawlai	Jowai	Raliang
Estimated soil moisture by *ANN1* in percentage	33.4	28	30.8	32
Measured soil moisture in percentage	38	26	35	30
Percentage Error	-12.1	7.7	-12	6.7

Table 6.5: Accuracy of *ANN 2* in estimating soil moisture for '*Gradient descent with adaptive learning rate*' algorithm and '*Elliot symmetric sigmoid*' transfer function

Places	Mawlynrei	Mawlai	Jowai	Raliang
Estimated soil moisture by *ANN2* in percentage	34.5	28.4	30.6	27.8
Measured soil moisture in percentage	38	26	35	30
Percentage Error	-9.3	9.1	-12.5	-7.3

Table 6.6: Accuracy of *ANN 2* in estimating soil moisture for '*Levenberg-Marquardt optimization'* algorithm and '*Linear'* transfer function

Places	Mawlynrei	Mawlai	Jowai	Raliang
Estimated soil moisture by *ANN2* in percentage	36.2	27.4	38.2	26.8
Measured soil moisture in percentage	38	26	35	30
Percentage Error	-4.7	5.5	9.2	-10.7

The actual and ANN estimated soil moisture values are shown in the form of bar diagrams in Figures 6.6 and 6.7 for *ANN 1* and *ANN 2* respectively, with the configurations having the training algorithms and transfer functions as shown in the figures.

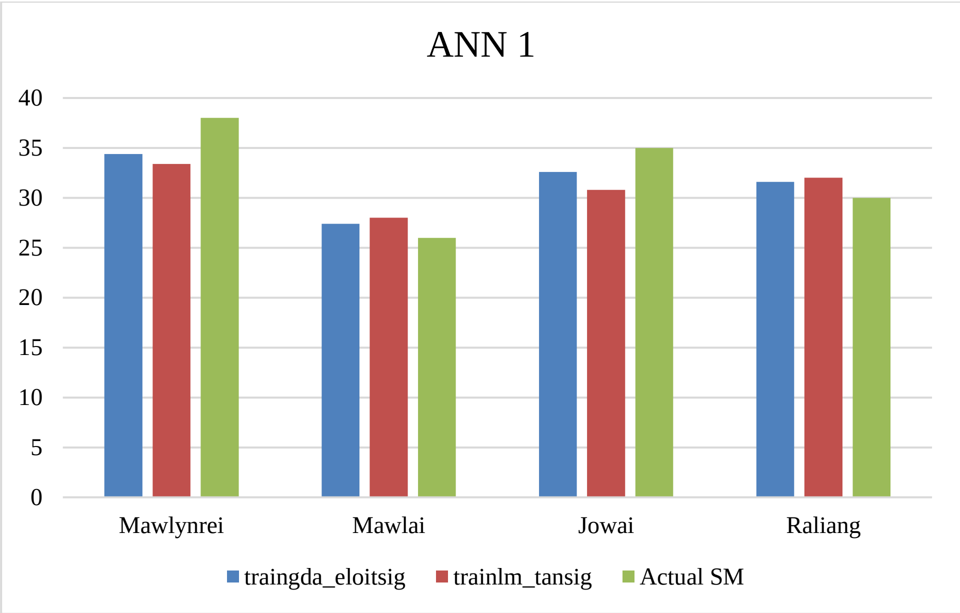

Figure 6.6: Bar-graph between actual and estimated soil moisture values for *ANN 1*

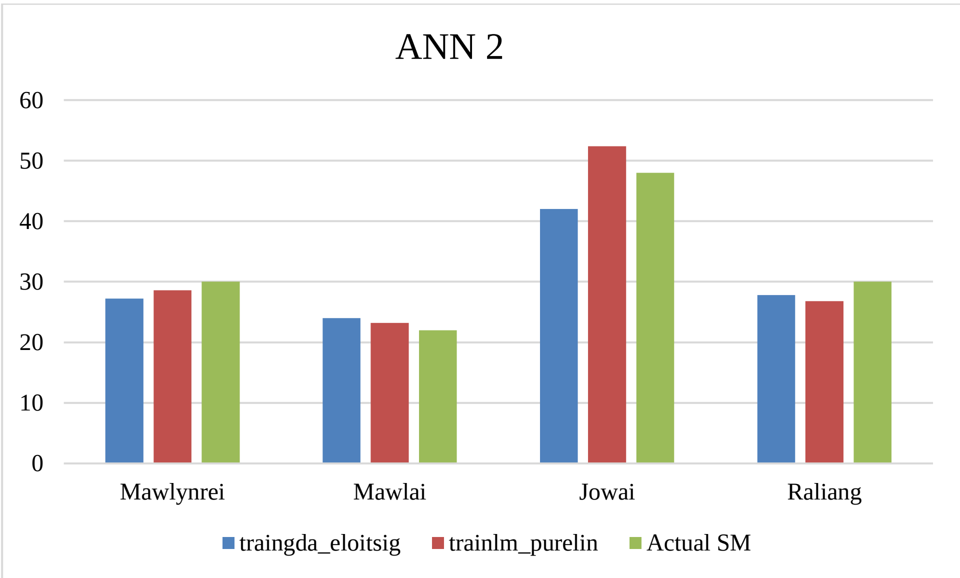

Figure 6.7: Bar-graph between actual and estimated soil moisture values for *ANN 2*

It is seen from the bar diagrams that the *ANN 1* gives near accurate results for the following combinations of transfer functions and learning algorithms-

(a) Elliot symmetric sigmoid transfer function and Gradient descent with adaptive learning rate algorithm. Average error in estimation is 10.5%.

(b) Symmetric sigmoid transfer function and Levenberg-Marquardt optimization algorithm. Average error in estimation is 13.2%.

Similarly it is seen that *ANN 2* gives the near accurate results for the following combinations of transfer functions and learning algorithms-

(a) Elliot symmetric sigmoid transfer function and Gradient descent with adaptive learning rate algorithm. Average error in estimation is 6.6%.
(b) Linear transfer function and Levenberg-Marquardt optimization algorithm. Average error in estimation is 3.3%.

Thus *ANN 2* is found to be a better estimator because of the following reasons.

(i) It requires less number of inputs to estimate soil moisture.
(ii) It is more accurate in estimating soil moisture.

6.7 CHAPTER CONCLUSIONS

The accuracy levels for the first methodology which consists of 14 inputs for *ANN 1* and that of the second methodology which consists of only 3 inputs for *ANN 2* are same. However, *ANN 2* requires fewer inputs with same accuracy level. Hence, *ANN 2* can be considered as a more suitable method for measuring soil moisture. This method is highly useful for places having open water bodies, such as the North Eastern region of India, where the traditional soil moisture measurement methods fail to give soil moisture values with fair level of accuracy.

The outcomes of the study are enlisted as the following.

(a) Design of a soil moisture estimation system for places having large open water bodies.
(b) Design of a soil moisture estimation system using ANN, by taking microwave brightness temperature values as input.
(c) Determination of optimum amount of microwave data required for soil moisture estimation, using suitable configuration of ANN.