# BACKPROPAGATION NEURAL NETWORK FOR SOIL MOISTURE RETRIEVAL USING NAFE'05 DATA : A COMPARISON OF DIFFERENT TRAINING ALGORITHMS

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## ABSTRACT:

The backpropagation artificial neural network (ANN) is a well-known and widely applied mathematical model for remote sensing applications for pattern recognition, approximation and mapping of non-linear functions and time-series prediction. The backpropagation ANN algorithm is underpinned by a gradient descent algorithm that is used to modify the network weights to maximise performance, using some criterion function. There are a number of variations from this general algorithm and it is necessary to explore these to find the best method for any particular application. The application considered in this paper is the determination of volumetric soil moisture content given airborne microwave measurements of the H- and V-polarized brightness temperature obtained during the National Airborne Field Experiment 2005 (NAFE'05). In this paper, a number of backpropagation ANN methods are investigated. Some produce the globally acceptable accuracy of less than or equal to 4%v/v of Root Mean Square Error (RMSE). However, the standard deviation among the 11 different variations of backpropagation training algorithms (0.55) is significant compared to the accuracy. Hence, there is a need for a full analysis of the backpropagation ANN and careful selection of the best backpropagation ANN model to be used.

## 1.INTRODUCTION

Soil moisture in the top few centimetres is an important variable which governs the partitioning of rainfall into run-off or infiltration. Obtaining this value accurately is important in the prediction of erosion, flood or drought. The most accurate way of obtaining this value is through actual in-situ field measurements but this technique is very time and cost consuming especially for large scale soil moisture retrieval. Microwave remote sensing, either active or passive, has been utilized and has shown the greatest success in estimating soil moisture in a temporally and spatially consistent manner [1].

Passive microwave radiation in the L-band for soil moisture retrieval is actively being explored because the effect of the atmosphere is small and can be modelled and predicted. Moreover the vegetation attenuation at L-band frequencies is minimal. Passive microwave radiometer measures the thermal emission from the surface. The intensity observed is proportional to the product of soil temperature and the surface emissivity. This product is called the brightness temperature (Tb) [2]. The soil emissivity at microwave wavelengths is a strong function of its moisture content because of the large dielectric contrast between dry soil and water. The relationship between the soil moisture and the received radiation is non-linear, ill-posed and complex [3].

Artificial Neural Network (ANN) is a model-free estimator as it does not rely on an assumed form of the underlying data [4]. Using some of the observed data, the ANN will try to obtain an approximation to the underlying system that generates the observed data through a process called learning by example. This is a method which is based on very sound mathematical principles and it has proved very successful in developing computationally efficient algorithms for geophysical applications like satellite remote sensing, meteorology, oceanography, numerical weather prediction, and climate studies. A type of ANN, the multilayer perceptron trained by a backpropagation algorithm has been utilized successfully for soil moisture retrieval. Examples include using an Error Propagation Learning Back Propagation (EPLBP) neural network to retrieve soil moisture from simulated brightness temperature [5], the use of multi-frequency microwave radiometer for retrieving soil moisture profile using backpropagation neural network to retrieve soil moisture [6], and using a backpropagation neural network and Levenberg-Marquardt training algorithm to classify and retrieve soil moisture and soil temperature profile using remotely sensed data [7].

Standard backpropagation refers to the gradient descent algorithm based on the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function[8]. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. There are a number of variations on the basic algorithm that are based on other standard optimization techniques. A review of the literature reveals that there is a need for comparison of these algorithms to determine the best backpropagation training algorithm in terms of the accuracy of the final result. This paper presents a comparison of the accuracy of soil moisture retrieval using the different variations on the standard backpropagation algorithm provided by MATLAB Neural Network Toolbox [8].

## 2. DATA

This study uses the National Airborne Field Experiment 2005 (NAFE'05) data in the Goulburn catchment, south-eastern Australia, in November 2005. This month-long field experiment provided extensive airborne passive microwave observations together with spatially distributed and in-situ ground monitoring of soil moisture [9]. The area monitored was a square of approximately 40x40km divided into two sub-areas namely the Merriwa area on the east side of this square and the Krui area to the west (Figure 1).

During the field experiment, a small, two-seater plane from the Airborne Research Australia National facility called the Small Environmental Research Aircraft (SERA) was flown [10]. This aircraft was equipped with the Polarimetric L-band Multibeam Radiometer (PLMR) and thermal imager. The PLMR obtains data of both H- and V-polarized brightness temperatures (Tb) using a single receiver with a polarization switch at incidence angles +/-7°, +/-21.5° and +/-38.5° in either across track (push-broom) or along track configurations. The aircraft was flown at four different altitudes over either Krui or Merriwa area and resulted in four different ground resolutions of: (i) 1km, (ii) 500m, (iii) 250m and (iv) 62.5m.

Near-surface soil moisture data were measured across the NAFE'05 study area at a range of spatial scales. During the four weeks experiment, the near-surface soil moisture data was measured across the eight focus farms (Figure 1) concurrently with the aircraft overpasses. At the focus farms, soil moisture measurements were taken at many locations within the farm at various resolutions: 500m, 250m, 125m, 62.5m, 12.5m and 6.25m.

For the purpose of this study, the focus farm Roscommon in the Krui area with the characteristics in Table 1 is used. The airborne data with ground resolution of 250m is utilized.

| Area(ha) | Topography | Landuses | Soils |
|---|---|---|---|
| 940 | Flat/Gently rolling | Grazing | Red basaltic clays and sandy soils |

Table 1. Main Characteristics of the Roscommon focus farm.

## 3. BRIEF DESCRIPTION OF BACKPROPAGATION NEURAL NETWORK MODEL

The Artificial Neural Network (ANN) was inspired by investigations into the structure of the human brain that consists of interconnected neurons. An ANN is made up of interconnecting artificial neurons within input, hidden and output layers. It has two modes of operation: training mode and operation/testing mode. In the training mode, neurons are trained using a particular input pattern to produce the desired output pattern. In the operation/testing mode, when a taught input pattern is detected at the input, the ANN will produce its associated output. A Backpropagation or feed-forward backpropagation ANN consists of two processing parts within its neurons: forward and backward. When an input pattern is fed to the ANN during its training process, the ANN will try to learn and compare its predicted output value with the desired output value. The errors between the predicted and actual valued are then ``backpropagated" through the network, and a gradient descent algorithm used to adjust the weights in the hidden and output layer nodes. The result is a network that produces the mapping between the input values and the output values via the neurons.

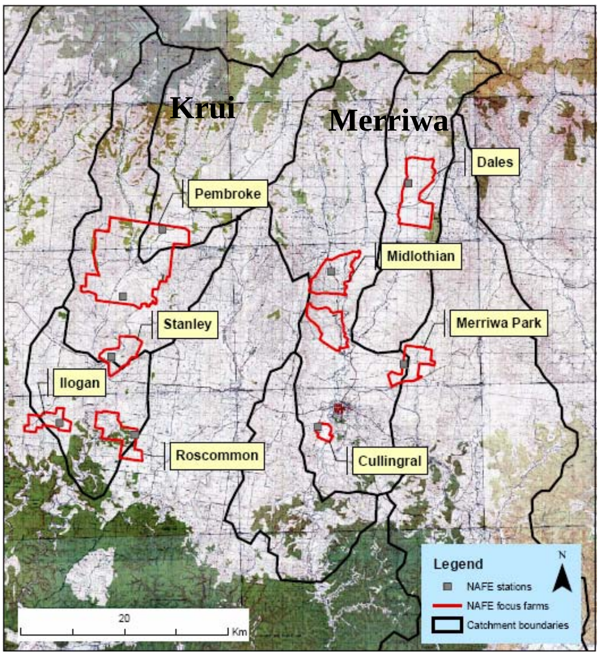


Figure 1. The NAFE'05 study area in the Goulburn catchment. The focus farms within the two sub-areas of this catchment are also shown.

62.5m footprint sizes. The area was entirely mapped at a particular altitude before descending to subsequently lower altitudes.

For the purpose of this study, the two-layer backpropagation ANN is being used. The architecture of this backpropagation NN is two inputs at the input layer, 4 neurons in the one hidden layer and one output at the output layer. The input of the backpropagation NN model is the H- and V-polarized brightness temperature value. The output of the NN model is the volumetric soil moisture data. The ANN is trained to generate a mapping between the continuous input brightness temperature values and the continuous output value of soil moisture data.

## 4. GROUND DATA

The soil moisture within the top 5cm of the soil profile was monitored coincident with each aircraft flight either across the entire area or across the focus farm. Measurements of the top 5cm soil moisture content were undertaken using an innovative Hydraprobe Data Acquisition System developed by The University of Melbourne that integrates a Global Positioning System and soil moisture sensor with a Geographic Information System [10]. During the sampling of the focus farms, very high resolution sampling was concentrated on a 150x150m area where soil moisture was measured at 12.5m (outer section) and 6.25m (75m inner square) spacing. The area surrounding the very high resolution sampling areas was sampled at intermediate resolutions (125- to 250-m spacing). The remaining extent of the farm area was sampled at coarser resolution of 500m and/or 1km spacing.

## 5. MODEL INPUT DATA

The Tb information collected from the aircraft, in its raw form, includes latitude and longitude using Geocentric Datum of Australia 1994 (GDA 94) coordinates, brightness temperature value (H-polarized, TbH and V-polarized, TbV), altitude and beam ID. The altitude is used to determine the ground resolution required and the beam ID is used for correcting to a common incidence angle. For this study, the incidence angle is corrected to +/- 38.5° as this is a typical value for many satellite systems. The medium resolution mapping with a flight altitude above sea level (ASL) between 1050m to 1270m at Roscommon focus farm was used. This results in a nominal ground resolution of 250m. The Tb data and the ground sampling soil moisture data used are first georeferenced to the same coordinate system (Universal Transverse Mercator, UTM). A regular grid was created as the reference grid for the data. These grids divide the area of interest into 250 x 250m square cells. Each cell of the grid is next assigned a value of H-polarized brightness temperature (TbH) and V-polarized brightness temperature (TbV) by averaging all the points falling into each cell (Figures 2 and 3).

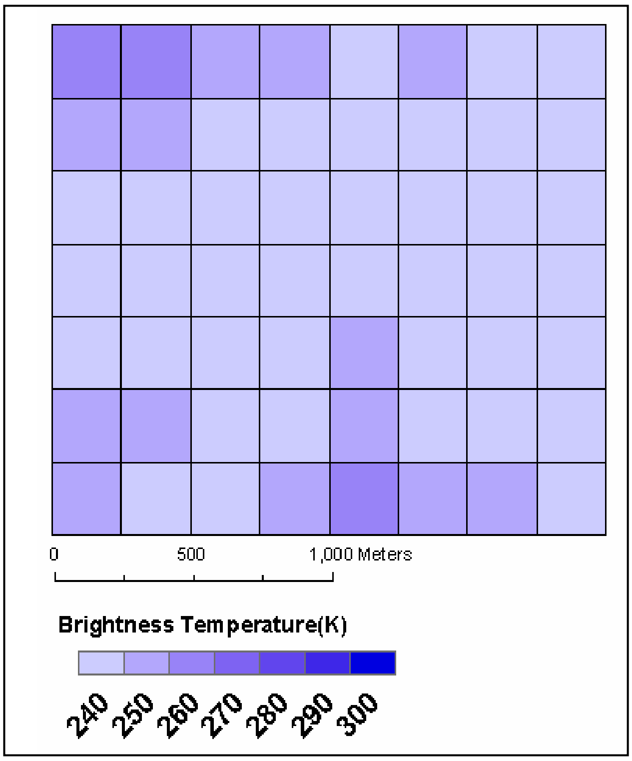


Figure 2. Aggregated H-Polarized brightness temperature at Roscommon on 8th November, 2005 using 250x250m grid cell.

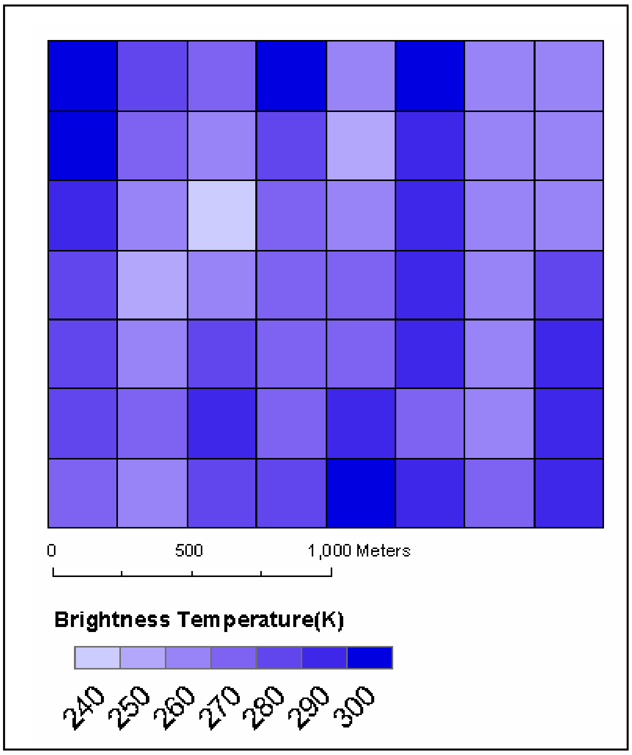


Figure 3. Aggregated V-Polarized brightness temperature at Roscommon on 8th November, 2005 using 250x250m grid cell.

## 6. TESTING AND RESULTS

The Roscommon data are first divided into three different groups or classes: low, medium and high, according to the maximum and minimum value of the TbH data. This is to ensure that the final data is distributed throughout the spatial location and is not gathered only for a certain TbH range. For each of the classes, the data are randomly divided into 60% for training, 30% for validation and 10% for testing the trained network. The validation set is used to stop the training of the NN when the NN begins to overfit the data. The test dataset is not used during the training and validation processes of NN construction but is used subsequently to test the trained NN. A general schematic of the division of the data is shown in Figure 4. The training, validation and testing set each contain values from the low, medium and high classes. During the training and validation processes, 10-fold cross validation is carried out whereby the training set and validation set are combined. During each run of the training process, a subset of this data will be used for validation while the remaining data will be used for training. The network is trained and validated using a basic ANN that uses backpropagation with gradient descent. The bias, layer weights and output weights of the network when it produces the lowest Root Mean Square Error (RMSE) for both the training and validation sessions are obtained. These values are then used for the training, validation and testing of the other backpropagation training algorithms using MATLAB. This means that these ANN starts from a good configuration. Table 2 shows the result of each of the backpropagation training algorithm.

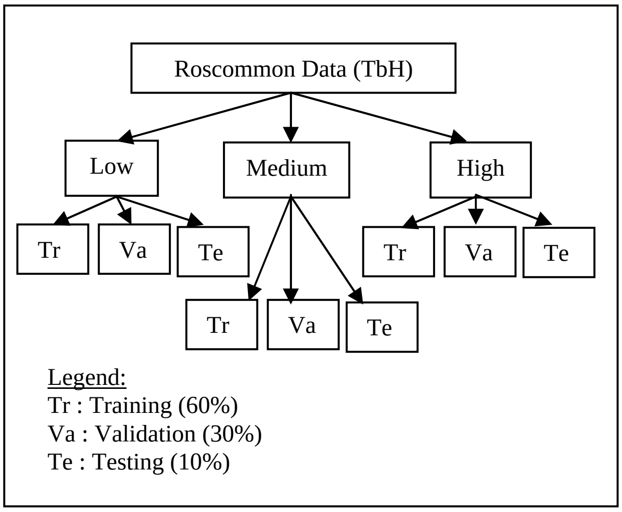


Figure 4. Schematic diagram shows the partition of the H-polarized brightness temperature (TbH) for the Roscommon area. The corresponding V-polarized brightness temperatures and the ground sampling volumetric soil moisture data are also obtained together with the TbH data.

| No. | Backpropagation Algorithm | RMSE (%v/v) |
|---|---|---|
| 1. | Batch Gradient with Momentum | 4.86 |
| 2. | Gradient Descent with Adaptive Learning Rate | 5.34 |
| 3. | Gradient descent with momentum and adaptive learning rate | 4.88 |
| 4. | Resilient backpropagation | 4.93 |
| 5. | Conjugate gradient backpropagation with Fletcher-Reeves updates **finish : epochs = 2* | 4.82 |
| 6. | Conjugate gradient backpropagation with Polak-Ribiére updates **finish : epochs = 2* | 4.83 |
| 7. | Conjugate gradient backpropagation with Powell-Beale restarts **finish : epochs = 2* | 4.83 |
| 8. | Scaled conjugate gradient backpropagation | 5.77 |
| 9. | Quasi-Newton Algorithm : BFGS | 3.93 |
| 10. | Quasi-Newton Algorithm :One step Secant Algorithm | 5.51 |
| 11. | Levenberg-Marquardt | 4.04 |

Table 2. Root Mean Square Error (RMSE) of soil moisture retrieval of various backpropagation training algorithms

## 7. DISCUSSION

Results obtained for RMSE are between the ranges of 3.93%v/v to 5.77%v/v. The globally accepted accuracy requirement for soil moisture retrieval is less than or equal to 4%v/v RMSE. With the same backpropagation NN architecture (same number of hidden layer, number of neurons in the hidden layer and same bias and weights value), it is shown that the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) Quasi-Newton algorithm is the only method able to retrieve the soil moisture with the required accuracy although the Levenberg-Marquardt method was close at 4.04%v/v. The scaled-conjugate algorithm has the worst result at 5.77%v/v. Interestingly, all of the methods produced results of a similar order of magnitude. The standard deviation of the ranges of accuracy obtained is 0.55, which is considered to be quite small, but for soil moisture retrieval this figure is quite significant. This means that the training algorithm when using backpropagation NN for soil moisture needs to be checked carefully before deciding on the algorithm to be used. The number of epochs required for each of the different backpropagation ANN to converge varies. The Conjugate Gradient backpropagation training algorithm converged in 2 epochs with an average RMSE of 4.83%v/v.

## 8. CONCLUSIONS

This paper has described initial results on the best backpropagation ANN to be used to model the relationship between airborne microwave measurements of brightness temperature and soil moisture content. A number of different backpropagation ANN methods have been explored with the main criterion for analysis being the RMSE between predicted soil moisture content and ground truth. Only one method produced results that meet the required 4%v/v criterion although a second method was close. Examining the standard deviation of the results across different training sets for the same ANN method reveals significant variations. The next step in the research is to explore the best ANN methods for additional areas within the NAFE test site and to investigate other available data that can be used to enhance the performance of the ANNs for the prediction of soil moisture content.

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