EFFECT OF ANCILLARY DATA ON THE PERFORMANCE OF LAND COVER CLASSIFICATION USING A NEURAL NETWORK MODEL

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1. Introduction

- Satellite images **alone** proven to be insufficient for separating land cover classes (Carpenter at al., 1997). An advantage of using multisource is that additional features can be incorporated in the classification. Ideally, each of the data sources have unique information contributing to the classification process.
- In particular, topographic variables in combination with imagery significantly enhance the separation of land cover types (Richetii, 2000; Pedroni, 2003).
- A difficulty for processing of multisource is the difference in measurement scales and feature distributions from various data.
- Statistical methods often cannot process multisource data because of their different distribution properties and measurement scales (Benediktsson et al., 1990).

- Therefore, a classification method that can deal with distribution-free and measurement scale-free issues are indispensable.
- Artificial neural networks (ANN) are among favorable methods for such kind of purpose, and they are able to integrate multisource data in the classification (Bischof et al., 1992).
- This study aims to examine the effect of combining satellite images and ancillary data on land cover classification performance using a multi-layer perceptron neural network.
- Tsukuba city is selected to conduct the investigation because it contains various patterns of land cover. In addition, the high-resolution image of the area is available for the validation of the result.

A view of complex landscape of the Tsukuba city

2. Methods

2.1 Remote sensing and ancillary data

- ALOS (Advanced Land Observing Satellite), multi-spectral advanced visible near infrared 2 (AVNIR2) sensor, acquired on 20 September, 2009.
- Four bands of the visible and infrared spectrum were used in the classification.
- Ancillary data are elevation, slope and normalized difference vegetation index (NDVI).

$$NDVI = (NIR_{band4}-RED_{band3})/(NIR_{band4}+RED_{band3}).$$

2.2 Reference data

- Secondary data was employed as reference data for classification and accuracy assessment . They are *existing land use map of 2008* and the *data of land use derived from the Google earth*.
-These data were used for identifying land cover types in the city, delineation of training areas and accuracy assessment.
- Land use/cover classes were identified using the Tsukuba land use/cover map of 2008 with a resolution of 10 m x 10m.

2.3 Network architecture (topology)

In order to examine the effect of combining ALOS and ancillary variables on classification performance, the land use/cover maps of the area were produced using different input combinations:

- ALOS alone (Bands 1, 2, 3 and 4): 4 inputs
- ALOS plus terrain (elevation and slope): 6 inputs
- ALOS plus terrain and NDVI: 7 inputs

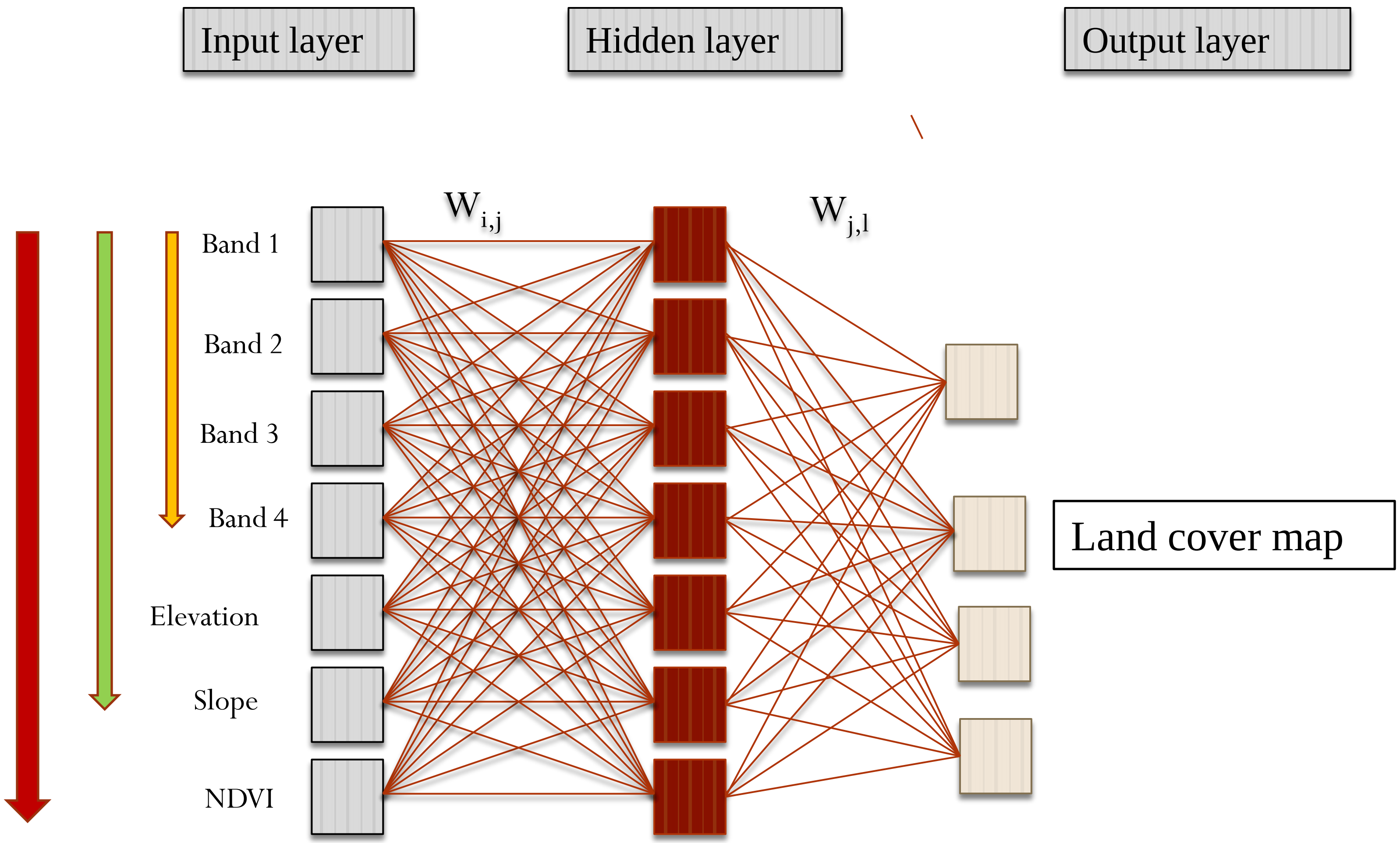

Figure 1: Network topology for land cover classification

2.4 Training the network for classification

- Training is to derive appropriate weights between the input and hidden layer and between the hidden and the output layer for classifying unknown pixels.
- The process is carried out by two steps: forward and backward steps.
- In the **forward step**, a single hidden layer node receives is weighted according to the following:

$$\boxed{net_j = \sum_{i=1}^{m} w_{ji} o_i} \longrightarrow o_j = f(net_j)$$

Activation function for non-linear mapping

where w_{ji} is the weight between node i and node j

o_i is the input from node i.

- As forward step is completed, the "computed output" is compared with their desired values, and error is computed. The error is then propagated **backward** through the network and the weights are corrected according to the **generalized delta rule** (Rumelhart at al., 1986).

$$\Delta w_{ji(t+1)} = \eta \delta_{ji} o_i + \alpha \Delta w_{ji(t)}$$

where w_{ji} is weight from input i to node j at time t,
η is learning rate, α is momentum, and δ is computed error.

- The **learning rate** controls the size of weight change. The forward and backward steps continue until the network has learned the characteristics of all classes.

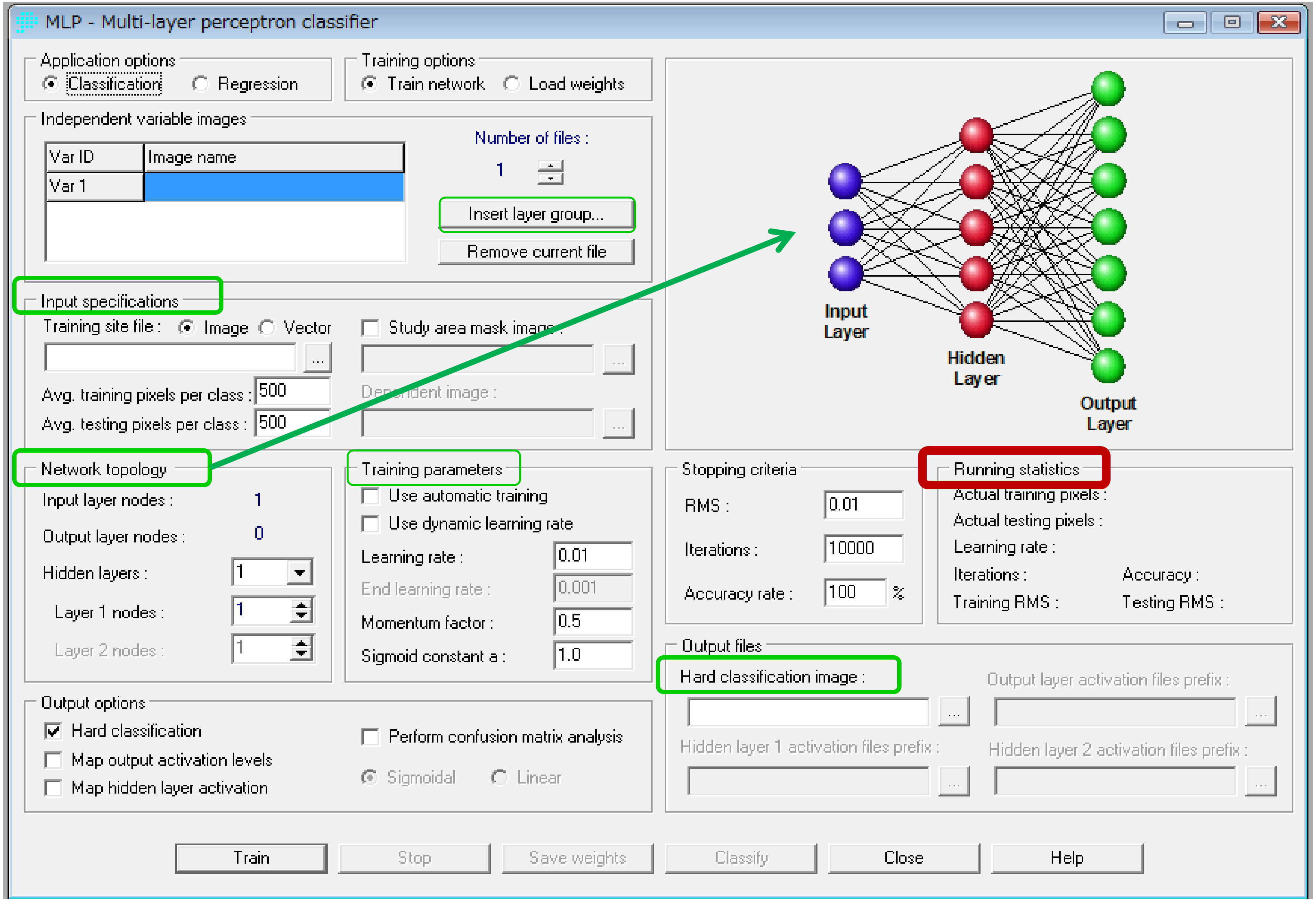

Figure 2: Interface of neural network for classification of satellite imagery

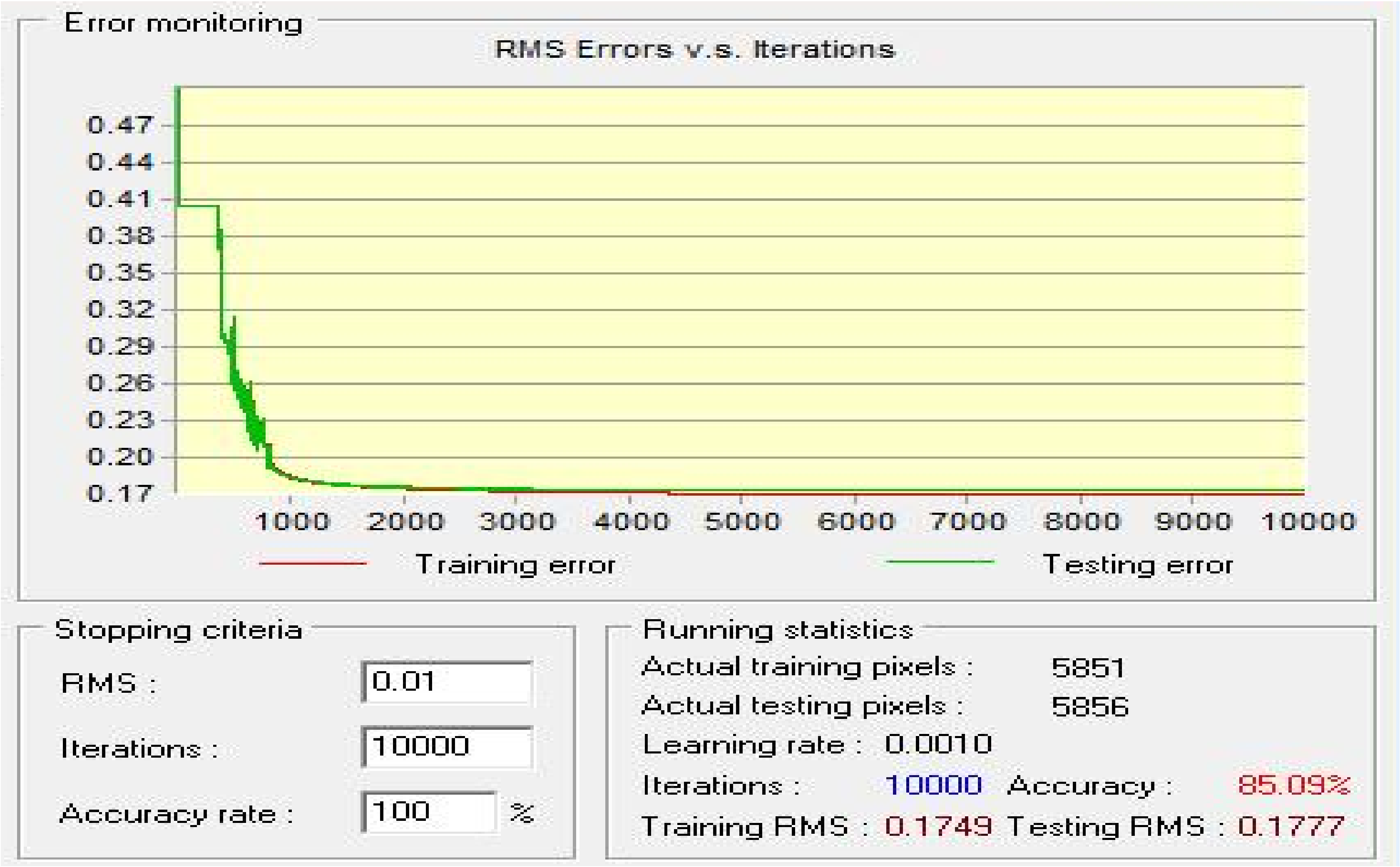

Figure 3: Classification with ALOS data alone

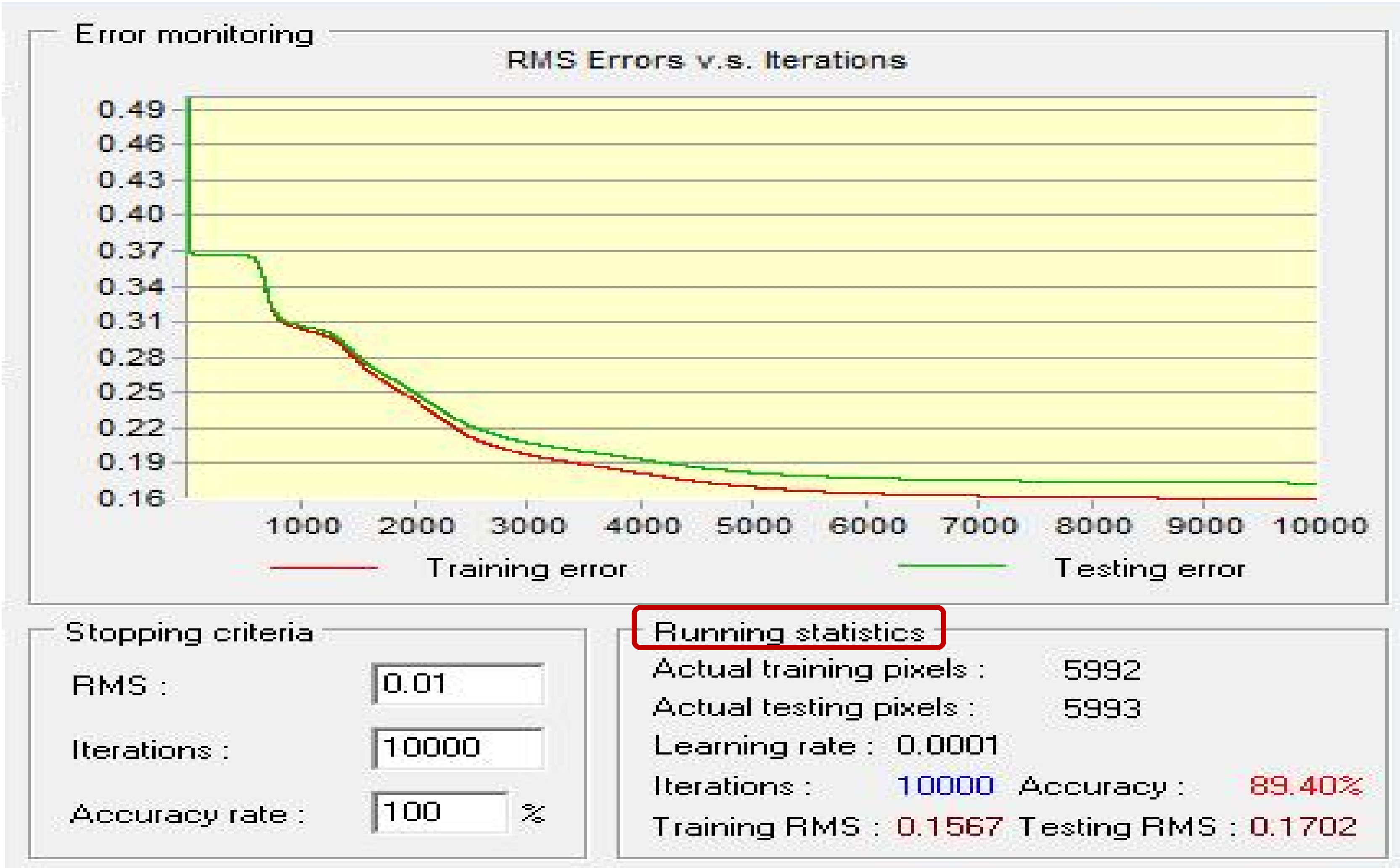

Figure 4: Classification with ALOS data, elevation and slope

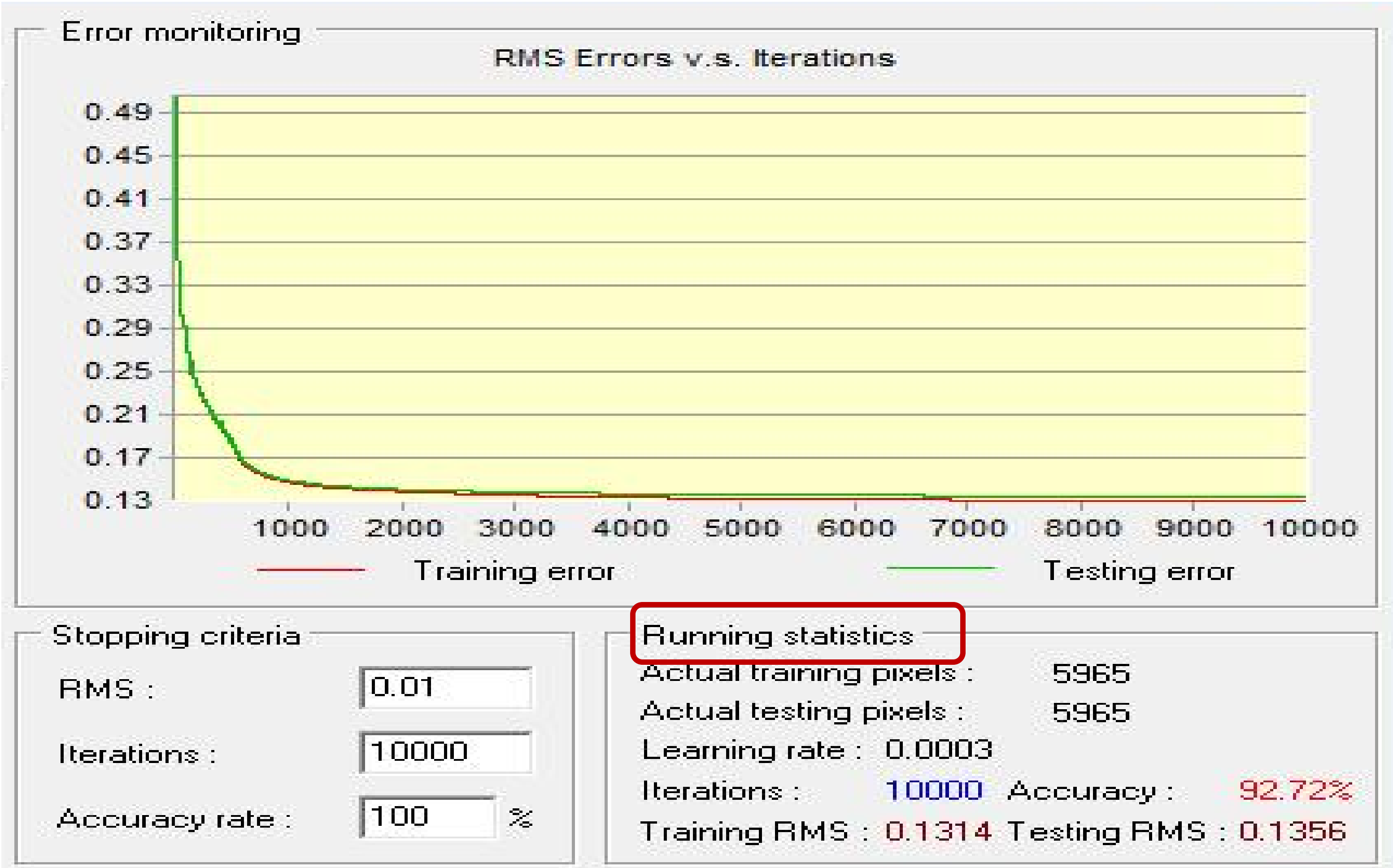

Figure 5: Classification with ALOS data, elevation, slope and NDVI

2.5 Accuracy assessment

- A set of 142 pixels were collected for accuracy assessment using UM_FieldGIS, embedded Google Map API, developed by Dr. Ko Ko Lwin.

- The error matrices for the classifications were generated by visually and carefully interpreting each sample pixel.

Figure 6: Forest in city area

Figure 7: Farmland

Figure 8: Paddy field

Figure 9: Urban/built in area

3. Results

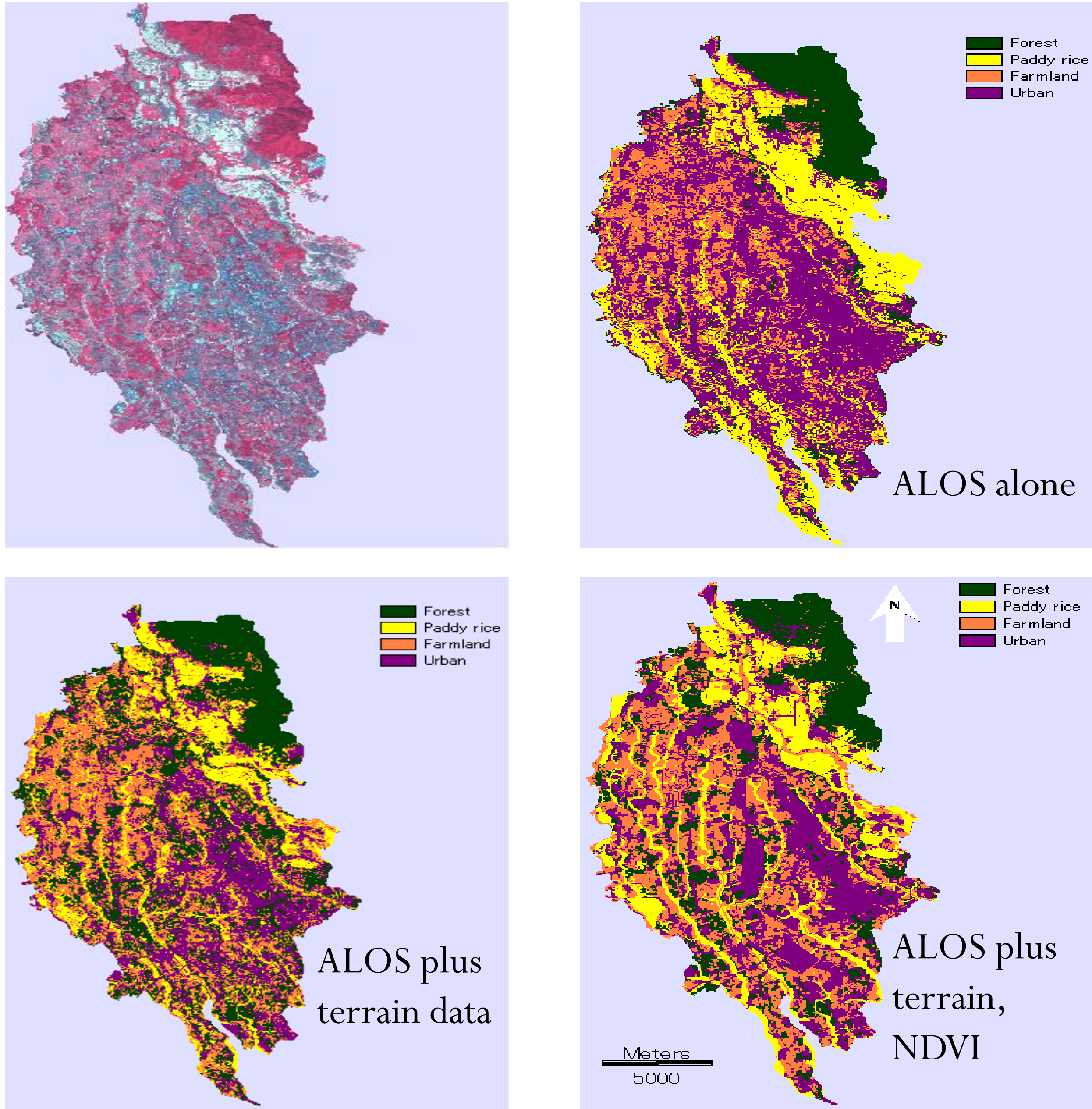

Figure 10: Land cover maps derived from different input combinations

Table 1: Effect of ancillary data on spatial extent of land cover

Land use/cover	Extent of land cover types of different classifications in percentage		
	ALOS data alone	ALOS and terrain data	ALOS, terrain and NDVI data
Forest	**17.05**	**18.09**	**20.14**
Paddy rice	18.25	18.01	18.77
Farmland	**39.21**	**38.07**	**36.02**
Urban	25.49	25.83	25.07
Total	100.00	100.00	100.00

Table 2: Error matrix for accuracy assessment of land cover map using ALOS data alone

	Reference data					
Classified data	Forest	Paddy rice	Farmland	Urban	Total	U.Acc
Forest	31	1	2	3	37	83.78
Paddy rice	3	34	1	0	38	89.47
Farmland	3	4	25	0	32	78.13
Urban	0	4	5	26	35	74.29
Total	37	43	33	29	**142**	
P.Acc	83.78	79.07	75.76	89.66		
Overall accuracy	**81.69**					
Kappa index	**0.78**					

Table 3: Error matrix for the accuracy assessment of land cover map using ALOS and terrain data

	Reference data					
Classified data	Forest	Paddy rice	Farmland	Urban	Total	U.Acc
Forest	31	1	3	2	37	83.78
Paddy rice	2	34	2	0	38	89.47
Farmland	1	4	27	0	32	84.38
Urban	0	1	5	29	35	82.86
Total	34	40	37	31	**142**	
P.Acc	91.18	85.00	72.97	93.55		
Overall accuracy	**85.21**					
Kappa index	**0.82**					

Table 4: Error matrix for the accuracy assessment of land cover map using ALOS, terrain and NDVI

	Reference data					
Classified data	Forest	Paddy rice	Farmland	Urban	Total	U.Acc
Forest	33	1	1	2	37	89.19
Paddy rice	2	35	1	0	38	92.11
Farmland	1	3	28	0	32	87.50
Urban	0	0	2	33	35	94.29
Total	36	39	32	35	**142**	
P.Acc	91.67	89.74	87.50	94.29		
Overall accuracy	**90.85**					
Kappa index	**0.89**					

4. Discussion

- Topographic data and NDVI in combination with ALOS imagery improved significantly the classification accuracy from **81.69 % to 90.85% in the study area (9.16%)**.

- Comparing with other studies:

Franklin (1987) integrated topographic variables as additional bands into Landsat images in a mountainous area of Canada's Yukon. The overall accuracy of land cover map improved from 46% to 75%.

Maselli *at al*. (1995) incorporated terrain and soil data with Landsat TM in a classification in Tuscany, Italia. Kappa of the classification result increased from 0.744 (Landsat data alone) to 0.91 (integration of terrain, soil and Landsat images).

Harris and Vantura (1995) combined zoning and housing data with TM images. The overall classification accuracy increased by 10%.

- ANN have the advantage of overcoming the difficulty in merging data from multiple sources because they are distribution-free, that is, it is not required to model the data with a specified distribution. The technique allows remotely sensed and ancillary data layers to be integrated for the purpose of accuracy improvement.
- More improvement may be expected using additional information such as the texture, the shape and the size of the objects in the urban setting.

Thank you for your kind attention!