CHAPTER 5

SUMMARY AND CONCLUSIONS

The Advanced Microwave Sounding Unit-B (AMSU-B), flying on the NOAA-15 and 16 satellites, is the new generation of a series of microwave imager/sounders than can sense atmospheric moisture and precipitation through clouds. In this thesis, we have examined how the AMSU-B data can be applied to all-weather systems analysis. We presented 1) the signatures of hydrometeors (precipitation and non-precipitation) in AMSU-B data, using visual inspection and quantitative measurements as well. 2) classification and distinguishing of hydrometeors using AMSU-B data and by artificial neural networks (ANNs) and statistical methods as well. 3) estimating of water vapour in terms of mixing ratio using AMSU-B data by Artificial neural network and multi-regression method also. Several conclusions can be drawn from this work.

The results of visual inspection suggest that the detection of the signatures and also intensities of heavy and moderate precipitating hydrometeors (thunderstorms and heavy rain, moderate rain and snowfall) as well as snow covered and upper level moist regions, in AMSU-B images, are warranted. Signatures of low precipitating hydrometeors (light rain) and non-precipitating hydrometeors (low level moisture) at 89 GHz may be little difficult, but measurements at 150 and 176 GHz show promise in detecting of non-precipitating hydrometeors. These frequencies are very sensitive to smaller sized ice particles than 89 GHz due to their shorter wavelengths (e.g. ~ 2 and 1.7 mm versus ~ 3.37 mm). An estimate of three dimensional structures of moisture and hydrometeors can be derived from AMSU-B data.
The results of quantitative measurements of brightness temperature suggest that the signatures of different hydrometeors are sufficiently reliable (almost always beyond 1 s confidence level). The distinguishing points, for this type of analysis, are: (a) brightness temperature at 89 GHz, (b) slopes between 89 and 150 GHz and (c) crossover of brightness temperature curves at 183 GHz with respect to 89 GHz. Different meteorological situations are seen to be divided into three groups: group I: The events with quite low brightness temperatures (< 220 K) at 89 GHz and related to heavy precipitating hydrometeors (thunderstorm, heavy rain) and snow cover. Group II: All low and moderate precipitating hydrometeors (light and moderate rainfall and snow fall shows fall in average brightness temperature between 89 and 150 GHz. Group III: All non-precipitating hydrometeors (moisture and clouds at different altitudes) shows rise in average brightness temperatures between 89 and 150 GHz.

It is felt that using these quantitative signatures one can "see remotely" the present weather situation anywhere at meso-scale (few pixels data is taken at the event-station), and hence can be of help for "operational forecasters" for his predictions, and a useful tool for air traffic planning.

The results of artificial neural networks for recognitions and classifications of hydrometeors indicate that use of ANNs for meso-scale weather analysis using multi-spectral, high resolution microwave satellite data has a good classification capability and hence good prediction-potential for finding different meteorological events (like thunderstorms). In general the error in classification is not completely unexpected.

The first and foremost reason for misclassification is the classification itself uses fuzzy logic words (though meteorologists do make attempts to quantitatively them to a certain limit).
The second equally important reason behind this misclassification can surely be time-difference between IMO reports and AMSU-B passes. During this time difference the meteorological conditions can change sufficiently to go from, for example thunderstorm to heavy rain.

The third reason, of course, is the uncertainty in brightness temperature itself, relating meteorological conditions and associated vertical variations of hydrometeors.

And the fourth reason, training data must be adequately extensive and representative and must fully represent all cases about which the network will be required to generalise from. If both these conditions are satisfied, and the network is trained with a suitable training algorithm, then the performance of the network will be good.

The results for water vapour retrieving indicate that, overall, neural network estimates was superior to the conventional methods (e.g. multi regression) estimates, and the results seem reasonable for below 500 hPa atmospheric levels. We might expect, because the ANN was trained using a very limited amount of data for each month, especially for Tehran, the model is currently may not be able to recognize and account the details of seasonal shifts in meteorological regimes, especially for 500 and 400 hPa. Although removing the surface parameters is able to somewhat correct for these weaknesses of the model, especially for combined model, we should expect that further improvements in the performance could be achieved by using more extensive and varied datasets for training and by incorporating other data sources as input variables. Further work is ongoing to identify which input variables will be most informative with regard to the estimation of mixing ratio from combination of remotely sensed AMSU-B channels and combinations with the other readily available data sources for a specific level of the atmosphere.