ANSER -- ARTIFICIAL NEURAL NETWORK EXPERT SYSTEM FOR SATELLITE-DERIVED ESTIMATION OF RAINFALL

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ABSTRACT:

This research presents an artificial neural network expert system technique for rainfall estimation from satellite data. An ANSER-Artificial Neural network expert system for Satellite-derived Estimation of Rainfall is being developed in the NOAA/NESDIS/ SAL. Using the ANSER technique, estimation or computation of rainfall amounts will be 10 times faster. The average error of rainfall estimates for the total precipitation event will be reduced to less than 30%, the currently achievable accuracy. This research work will be a big step toward creating an rainfall estimation expert system using an artificial neural network from the remotely-sensed data.

KEY WORDS:

Artificial Neural Network, Expert System, Rainfall, Satellite-derived, Estimation

* This work was done while the author held a USA National Research Council Postdoctoral Research Associateship at the National Oceanic and Atmospheric Administration (NOAA), National Environmental Satellite, Data, and Information Service (NESDIS), Satellite Application Laboratory.

1. INTRODUCTION

Assessment of global climate change is a very important research area for the future of man and his environment. Rainfall estimation is a key parameter in this research. During the past 20 years, there has been a great increase in our understanding of how satellite data can be used to estimate rainfall. But, even with the use of interactive computer systems, the time needed to prepare estimates of rainfall is about a half hour. Verification results show that the average error for an event is about 30%.

Some Artificial Intelligence (AI) systems for weather forecasting have been designed to be objective and automated (Zhang and Scofield, 1992); others are designed to augment human skill. In the Knowledge Augmented Severe Storms Predictor (KASSPr) system (Bullas, 1990), knowledge was elicited in a series of interviews and exchanges of documentation between the developer and an expert in severe weather forecasting. The Convex system (Weaver, 1987) first uses as automated analysis of the Denver morning sounding, combined with estimates of expected afternoon temperature and dewpoint, to determine the relative instability of the host air mass and its likelihood of initiating convection later in the day over the region of interest. The knowledge base for the Willard system (Zubrick, 1985) is a structured hierarchy of 30 rules. Most of the rules were developed using the inductive generalization feature of Rule Master, an expert system shell. Several investigators showed that estimating rainfall from both geosynchronous and polar-orbiting satellite was feasible (Woodley, 1972). A complete review of rainfall schemes that use visible, infrared, or microwave satellite data is presented by Barrett and Martin (1981). Most of the important facts about rain clouds have been extracted for use in the present estimation scheme. Currently, satellite-derived precipitation estimates (Scofield, 1987) and 3-hour precipitation outlooks for convective systems, Extratropical cyclones, and tropical cyclones are computed on the NOAA/NESDIS Interactive Flash Flood Analyzer (IFFA) system and transmitted to National Weather Service Forecast Offices, and River Forecast Centers. However, this system permits the computation of rainfall estimates for only one convective system at a time. This is due to the considerable time needed for image processing, interpretation, and the computation involved in the estimation of rainfall. If there are several storms occurring, an automatic estimation technique would be useful in providing rainfall estimates for the entire country. Digital satellite data is used in the estimation process. Artificial neural network (ANN) techniques are explored as a possible improvement to current techniques. This research applies ANN techniques to the enhancement of knowledge for automatic rainfall estimation from satellite data.

ANN computing is an area that is receiving increased research interest. Since ANNs are massively parallel systems, ANN computers have tremendous speed and nonlinear advantages over traditional digital machines. Hopfield developed the first architecture of a ANN, the Hopfield network, (Hopfield, 1982). Carpenter (1989) had researched adaptive resonance theory (ART) architectures. A conventional ANN architecture is the Back Propagation (BP) ANN. Matsuoka (1989) introduced a new training model, the Integrated Neural Network (INN). INN can reduce training time for syllable signal processing. Linsker (1988) described a Self-Organized architecture in a perception network; this model can recognize special features of its environment, without being told which feature it should analyze.

In a study by Xie and Scofield (1989), where the Scofield/Oliver Technique was used, there were significant differences between the rainfall observations and the satellite-derived rainfall estimates. In this paper, ANN technique will be used for estimates of rainfall. The main research efforts developed in this paper are as follows:

(1) The architecture of the ANSER system for estimates of rainfall;
(2) The parallel and nonlinear reasoning networks for estimation of rainfall;
(3) 1/2 hour training algorithm of a reasoning network for estimates of rainfall;
(4) Several experimental results of estimating rainfall using the ANSER system.

2. ANSER TECHNIQUE

2.1 The Architecture of ANSER

The architecture of an ANSER for satellite-derived estimation of rainfall can be seen in Fig. 1. There are three parts of this architecture: (a) ANSER USER SYSTEM; (b) ANSER TRAINING SYSTEM; (c) ANSER CENTER SYSTEM. The ANSER USER SYSTEM has one or more user subsystem(s) based in the IBM PC for estimates by users. Each user subsystem consists of a training subsystem, weight base and estimate subsystem. The ANSER TRAINING SYSTEM has more than one training subsystems operating on the mainframe computer NCCF HDS 9000 for training weights of ANSER. Each training subsystem has first training, re-training and output result functions. ANSER CENTER SYSTEM receives satellite data based on the IBM RISC 520 for the experts and it has six parts: (a) display subsystem for output of rainfall estimates; (b) explanation subsystem that gives different classification to different data; (c) a reasoning network for rainfall estimation based on the input data and rule, model, and knowledge base; (d) rule bases, mode bases, and knowledge bases will save rule, model, and knowledge provided by the expert; (e) a training subsystem for getting suitable weights for the ANSER; (f) weight bases for keeping weights of ANSER. ANSER USER SYSTEM, ANSER TRAINING SYSTEM and ANSER CENTER SYSTEM communicate with each other using Ethernet. This architecture will be enhanced for application to derive estimation of rainfall from satellite data.

2.2 Architecture of Reasoning Network

The basic architecture of reasoning network for 1/2 hour satellite-derived estimation of rainfall can be seen in Fig. 2. This is a 3 layer artificial neural network that includes 7 input linear neurons, 30 hidden nonlinear neurons (divided into 2 layers) and 1 output nonlinear neuron. There are 345 weights in this network.

The artificial neuron is a unit that functions similar to the real neuron of human (in this paper, neuron means artificial neuron). The ANN is a system which consists of artificial neurons that are connected to each other by weights. The function of each nonlinear neuron is sigmoid and is given by:

$$Yj=1/(1+\exp(-\sum_{i=0}^{N}(Yi*Wij))).$$

where: Yj - the output of the j-th artificial neuron.
Wij - the weight connected the i-th artificial neuron with the j-th artificial neuron.
Yi - the output of the i-th artificial neuron.

When the ANN was described in this paper, the artificial neuron numbers of layer are different. However, three layers of structure are always used. Several basic structures of ANNs will be connected to each other to become reasoning networks and the basic structure of the ANSER system.

3. ANSER PERFORMANCE

3.1. Input and Output of Reasoning Network

The input and output of the reasoning network are as follows:

Input: G = (cloud top temperature + cloud growth factor)
or (cloud top temperature + strong divergence aloft)
RB = rain burst factor
OS = overshooting top factor
M = merger factor
SE = saturated environment factor
MC = moisture correction
S = speed of storm
Output: 1/2 hour Satellite-derived Estimation of Rainfall.

3.2 Training Algorithm of the Reasoning Network

The training algorithm of the reasoning network for 1/2 hour Satellite-derived Estimates of Rainfall are as follows:

(1) Set random values to all weights of the reasoning neural network.

(2) A special type or model of rainfall should be chosen. It means that the reasoning network will be trained for this special type or model of rainfall estimation.

(3) One case of rainfall which has the same type or model rainfall mentioned in (2) is chosen to train the reasoning network for getting convergence weights.

- (a) Using Scofield/Oliver Technique: The inputs of reasoning network are the 7 factors shown in the beginning of this section. The output of the reasoning network is: S/O E=[(G or RB)+OS+M+SE]*MC*S.
- (b) The reasoning network is trained. The convergence weights are the weights of the 1/2 hour Scofield/Oliver reasoning network.

(4) The same case of rainfall which has the same type or model rainfall mentioned in (2) is chosen again to re-train the reasoning network for getting convergence weights for this special type or model case of rainfall.

- (a) The weights of the 1/2 hour Scofield/Oliver reasoning network will be used firstly.
- (b) The inputs of reasoning network are the 7 factors based on the Scofield/Oliver Technique.

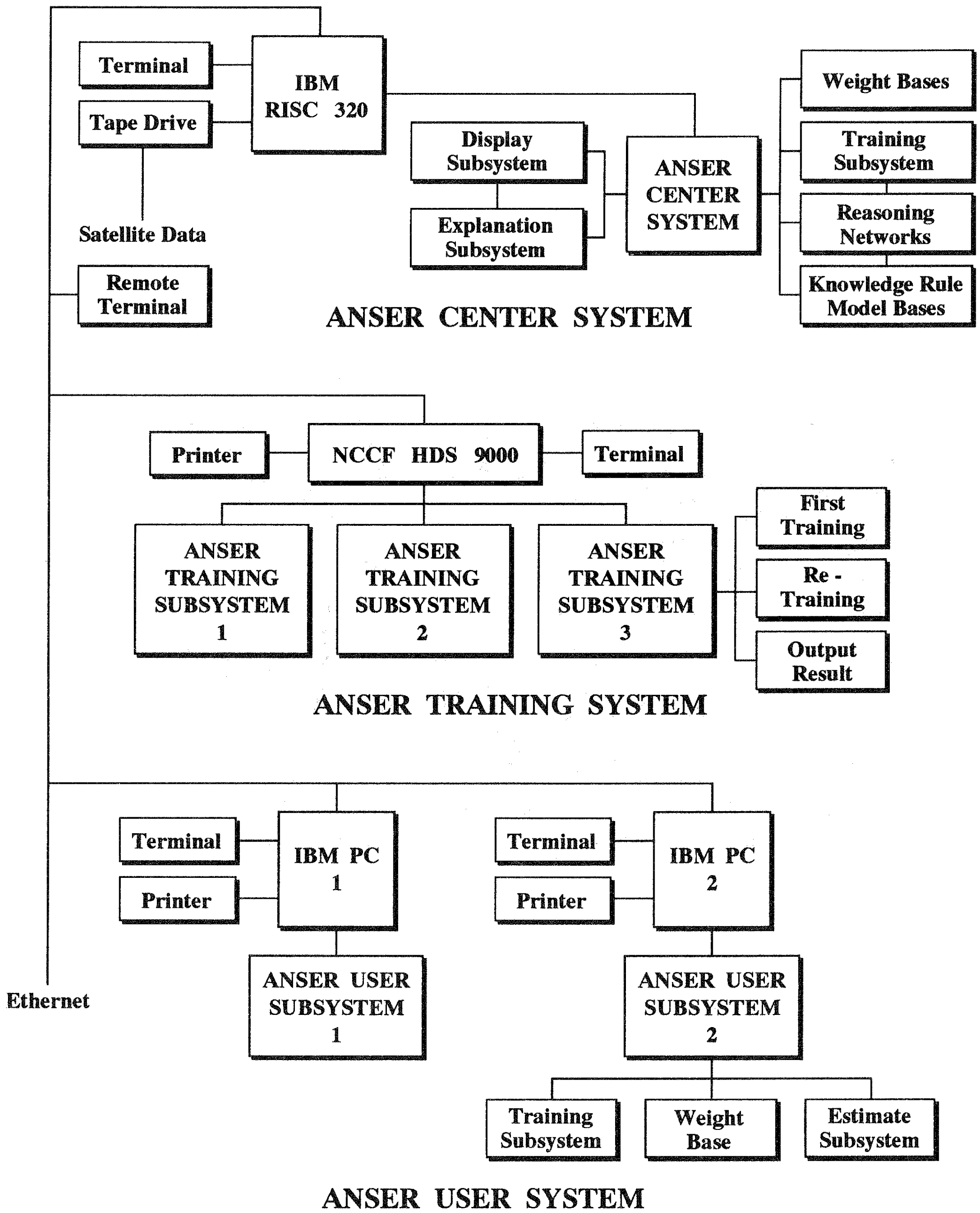
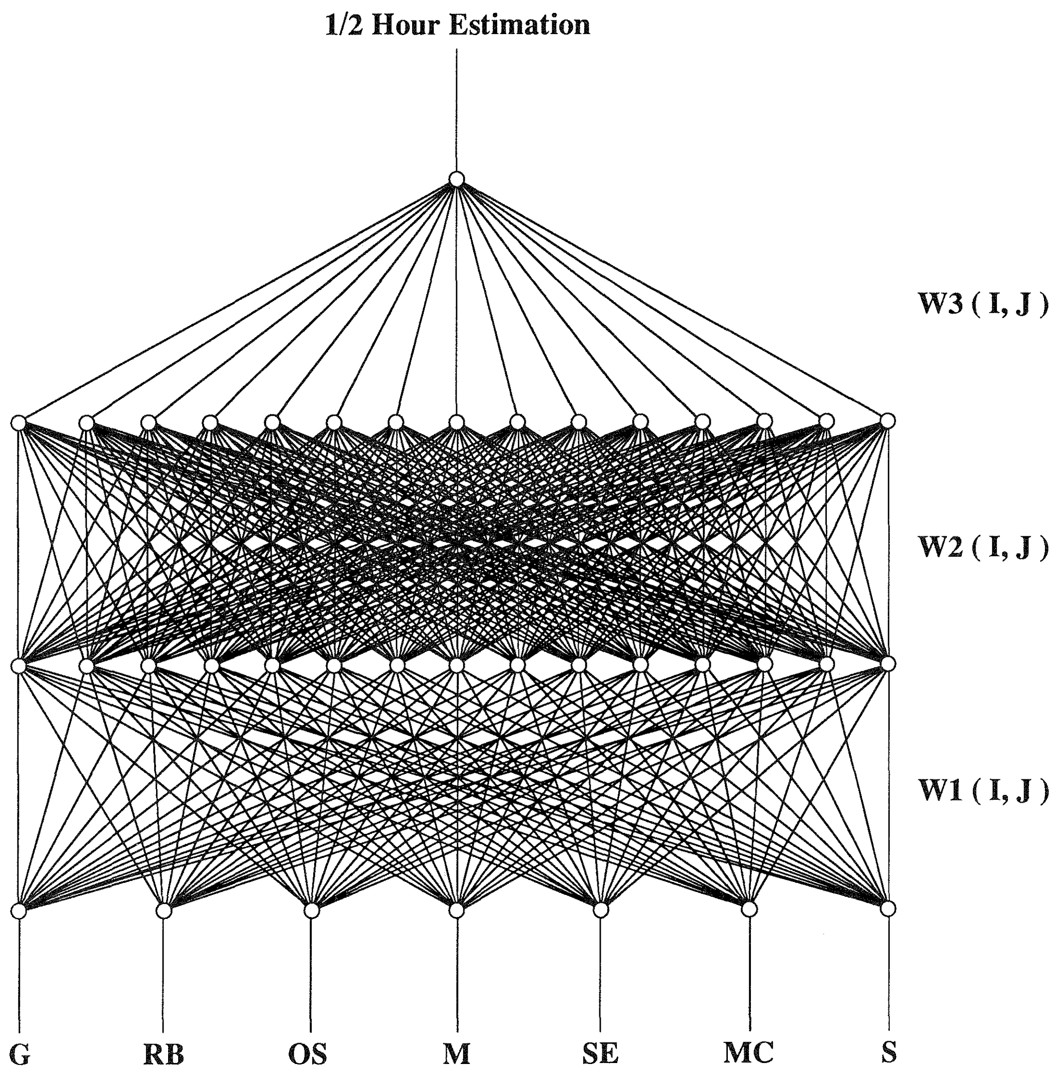


Figure 1 The Architecture of ANSER



—— Connection and Weight

o Artificial Neuron

Figure 2 The Architecture of 1/2 Hour Reasoning Network

(c) The first output of reasoning network is the output of the 1/2 hour Scofield/Oliver reasoning network.

(d) The next output of the reasoning network is a function of previous outputs of the reasoning network and observed data of this case.

(e) The reasoning network is trained. The convergence weights can be used as the weights for the 1/2 hour reasoning network for this special type or model of rainfall.

(5) Another case of rainfall which has the same type or model rainfall mentioned in (2) is chosen to retrain the reasoning network for getting convergence weights for this special type or model of rainfall.

(a) The weights of the 1/2 hour reasoning network derived previously will be used first.

(b) The inputs of the reasoning network are the 7 factors based on the Scofield/Oliver Technique.

(c) The output of the reasoning network is a function of previous output of the reasoning network and observational data for this case.

(d) This reasoning networks then trained. the new convergence weights can be used as the new weights of 1/2 hour reasoning network for this special type or model of rainfall.

(6) Repeat (5) until all the training samples are used for training this special type or model of rainfall reasoning network. The final trained result of the weights are the weights of 1/2 hour satellite-derived reasoning neural network for this special type or model of rainfall.

(7) Using the 1/2 hour satellite-derived reasoning neural network for testing the estimation of rainfall.

(a) A test case which has same type or model of rainfall has be chosen.

(b) The 1/2 Hour Satellite-derived Reasoning Network is run using the weights from (6) to obtain the estimation result.

(c) If the testing result is not good, the error is more than 10%, go back to (5) and the testing case will become another training case.

(d) If the testing result is good, error is less than or equal to 10%, go to (7) and test again.

4. RESULTS OF ESTIMATION

4.1 Experimental Results of the 1/2 Hour Mesoscale Convective Complex (MCC) reasoning Network

The experiment results of a 1/2 hour the MCC type reasoning network for the estimation of rainfall can be seen in Table 1. In this case, on July 19, 1985, a MCC located in IOWA (IA), USA. The observed rainfall was 9.5 inches.

The values of column S/O E are the results from the Xie/Scofield study (Xie and Scofield, 1988). The sum of the 1/2 hour estimates was 18.64 inches. The error (the difference between the observed data and the sum of the 1/2 hour satellite estimates) was +96.2%.

The values of column MCC E are the 1/2 hour estimates result from the 1/2 hour MCC reasoning network of the ANSER system. The sum of the 1/2 hour estimation data was 9.43 inches. The error is only -0.74%. In this case, after all information had been received, the satellite-derived estimation of rainfall only required 2 seconds of HDS 9000 CPU time to execute. Therefore the weights of the 1/2 hour MCC Reasoning Network of ANSER are very good for this type of event.

4.2 Experimental Results of the 1/2 Hour Multi-Clustered Linear (MCL) reasoning Network

The experiment results of a 1/2 hour the MCL type reasoning network for the estimation of rainfall can be seen in Table 2. In this case, on August 12, 1987, a MCL located in Kansas (KS), USA. The observed rainfall was 8.7 inches.

The values of column S/O E are the results from the Xie/Scofield study (Xie and Scofield, 1988). The sum of the 1/2 hour estimates was 6.038 inches. The error (the difference between the observed data and the sum of the 1/2 hour satellite estimates) was -30.6%.

The values of column MCL E are the 1/2 hour estimates result from the 1/2 hour MCL reasoning network of the ANSER system. The sum of the 1/2 hour estimation data was 8.53 inches. The error is only +1.92%. In this case, after all information had been received, the satellite-derived estimation of rainfall only required 2 seconds of HDS 9000 CPU time to execute. Therefore the weights of the 1/2 hour MCL Reasoning Network of ANSER are very good for this type of event.

Table 1

Testing Case — Satellite Derived Precipitation Estimates

No. 17 Data: July 19, 1985 Location: IA Types of MCS: MCC Observation: 9.5 Inch

TIME	CT	CG	DA	G	RB	OS	M	SE	MC	S	S/O E	S/O NE	MCC E
0230 - 0300	r. gray	.33 - .66		0.75					1.6	1	1.20		0.756
0300 - 0330	r. gray	.33 - .66		0.75					1.6	1	1.20		0.756
0330 - 0400	r. gray	decrease		0.30					1.6	1	0.48		0.424
0400 - 0430	r. gray	< .33		0.55				0.30	1.6	1	1.36		0.645
0430 - 0500	r. gray	same		0.40				0.30	1.6	1	1.12		0.528
0500 - 0530	r. gray	decrease		0.30				0.50	1.6	1	1.28		0.491
0530 - 0600	r. gray	< .33		0.45				0.50	1.6	1	1.52		0.601
0600 - 0630	r. gray	< .33		0.45				0.50	1.6	1	1.52		0.601
0630 - 0700	r. gray	< .33		0.40				0.50	1.6	1	1.44		0.562
0700 - 0730	r. gray	< .33		0.50				0.50	1.6	1	1.60		0.642
0730 - 0800	r. gray	< .33		0.55			0.50	0.50	1.6	1	2.48		1.090
0800 - 0830	r. gray	< .33		0.55				0.50	1.6	1	1.68		0.684
0830 - 1000	r. gray	decrease		0.3*3					1.6	1	1.44		1.272
1000 - 1030	black	decrease		0.20					1.6	1	0.32		0.378
Total (Inch)											18.64		9.43
Error (%)											+ 96.2		- 0.74

S/O E: Scofield / Oliver Technique Estimation; S/O NE: Scofield / Oliver Technique Network Estimation
MCC E: 1/2 Hour Mesoscale Convective Comples Type Reasoning Neural Network Estimation

Table 2

Testing Case   Satellite Derived Precipitation Estimates

No. 13   Data: Aug 12, 1987   Location: KS   Types of MCS: MCL   Observation: 8.7 Inch

TIME	CT	CG	DA	G	RB	OS	M	SE	MC	S	S/O E	S/O NE	MCL E
0730 - 0800	l. gray	< .33		0.15					1.1	0.5	0.083		0.148
0800 - 0830	r. gray	< .33		o.35			0.5		1.1	0.75	0.701		1.040
0830 - 0900	r. gray	< .33		0.35					1.1	0.75	0.289		0.382
0900 - 0930	r. gray	< .33		0.35					1.1	0.75	0.289		0.382
0930 - 1000	white	< .33		0.60					1.1	1	0.660		0.905
1000 - 1030	white	< .33		0.60					1.1	1	0.660		0.905
1030 - 1100	white	< .33		0.60				0.3	1.1	1	0.990		1.410
1100 - 1130	r. gray	< .33		0.35				0.3	1.1	1	0.715		1.070
1130 - 1200	r. gray	same		0.35				0.5	1.1	1	0.935		1.290
1200 - 1230	r. gray	decrease		0.30					1.1	0.75	0.248		0.304
1230 - 1300	r. gray	decrease		0.30					1.1	0.75	0.248		0.304
1300 - 1330	black	decrease		0.20					1.1	0.75	0.165		0.277
1330 - 1400	l. gray	decrease		0.10					1.1	0.50	0.055		0.116
Total (Inch)											6.038		8.533
Error (%)											- 30.60		- 1.92

S/O E: Scofield / Oliver Technique Estimation;   S/O NE: Scofield / Oliver Technique Network Estimation

MCL E: 1/2 Hour Multi-Clustered Linear Type Reasoning Neural Network Estimation

5. SUMMARY AND OUTLOOK

The use of ANSER for rainfall estimates is an important tool for the enhancement of accuracy for automatic rainfall estimation from satellite data. In this paper, the main research efforts focused on the development of:

(1) The architecture for the ANSER system for rainfall estimates;

(2) The parallel and nonlinear reasoning networks for the estimation of rainfall;

(3) A 1/2 hour training algorithm for the reasoning network to estimate rainfall;

(4) Several experimental tests of rainfall estimation using the ANSER system.

Because the ANSER is a massive parallel processing system, it makes estimating rainfall 10 times faster. In these cases, after all the information was received, the satellite-derived estimation of rainfall required about from 2 to 10 seconds of HDS 9000 CPU time to execute.

Because the ANSER is a nonlinear reasoning system, the average error of rainfall estimates is reduced to less than 30%, the currently achievable accuracy. In this work, the average errors of the rainfall estimates were always less than 10.0%.

Decision trees are series process techniques and run step by step and node by node. So decision tree techniques require more running time than that of parallel techniques. Decision trees are not able to use all rules, models, knowledge and factors that are stored in the different nodes at the same time. This is especially true when the rules, models, knowledge and factors are very complicated and nonlinear. So decision tree techniques always give "rough" results.

ANN techniques have demonstrated superior performance relative to classical methods for predicting the future behavior of a pseudo-random time series. There are many practical applications where, rainfall estimation and forecasting, can be of great value. Forecasting natural phenomena is a great area for using artificial neural network expert system techniques.

This study only considered rainfall estimation using the ANSER technique for some special cases. Further studies will consider the satellite signatures that comprise the convective rainfall estimation algorithm using ANN techniques.

ACKNOWLEDGEMENTS

The authors thank Donald B. Miller, Frances Holt, Joanna L. Newby, Tim Bellerby of Satellite Application Laboratory of NESDIS/NOAA for their constructive criticism, Juying Xie for providing satellite-derived input data and Dick Pritchard of Planning Research Corporation for providing satellite pictures, Paige Bridges for propagation of the illustrations, and Lori Paschal for typing the manuscript.

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