RADNET: A NEURAL NETWORK-BASED ESTIMATION OF THE SURFACE RADIATION BUDGET IN THE ARCTIC FROM TOVS HIRS AND MSU BRIGHTNESS TEMPERATURES

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1. INTRODUCTION

The lack of sufficient quantitative knowledge of the Arctic surface radiation budget has been identified as an obstacle to a better understanding of the arctic atmosphere-ice-ocean system within the global climate (WMO/WCRP, 1992). The U.S. interagency Surface HEat Budget of the Arctic Ocean (SHEBA) (Moritz et al., 1993) initiative identifies the documentation of the arctic surface radiation budget as one of its primary objectives. In particular, ice-ocean modeling studies typically use components of the surface radiation budget derived from rather crude parameterizations and climatologies. Data assimilation schemes designed to obtain statistics on the ice thickness distribution, an important climate indicator, require an ice growth rate that depends on the surface radiation balance. Climatological values of questionable quality are currently used to specify the surface radiation budget. In most cases these values do not vary in space, and vary in time only at a very coarse resolution. Even though long-term surface observations of radiative fluxes from Russian drifting stations exist, their spatial coverage is very limited. In order to construct two-dimensional fields of surface radiative fluxes, a satellite-based method is needed. In this paper we describe a method to derive downwelling longwave and shortwave fluxes in the Arctic from TOVS that employs a neural network to compute the relationship between HIRS and MSU brightness temperatures and radiative fluxes measured at the surface. Results and comparisons with surface observations from two field experiments, (LeadEx) and (CEAREX) are presented.

2. BACKGROUND

2.1 Surface radiation from space: physical vs. empirical methods.

One approach to obtaining radiative fluxes at the surface from satellites is to compute them from the vertical temperature and humidity profiles, cloud conditions, and surface properties using a radiative transfer model. Input variables for these computations are obtained from satellite radiances via algorithms and models. These algorithms are usually variations on the following components: a) scene identification (clear/cloudy), b) retrieval of surface radiative properties (temperature/reflectance), c) retrieval of column optical properties (atmospheric profile, cloud optical thickness, cloud height), and d) computation of downwelling surface radiation or flux profiles. This approach may be called "physical" even though the inversion of satellite radiances to obtain physical variables is commonly done using statistical techniques, and scene identification frequently includes the use of empirically determined thresholds (Rossow et al., 1990; Kergomard et al., 1993; Schweiger and Key, 1994).

An alternative approach is to relate observed top-of-the-atmosphere (TOA) radiances directly to simultaneous ground measurements of downwelling radiation. This is usually achieved through multiple regression techniques and is therefore often termed empirical or statistical (cf., Morcette and Deschamps, 1986; Schmetz, 1989). The physical approach appears more attractive because once the underlying physical principles are identified, it offers the opportunity for further development of the individual components and allows for direct comparison with variables calculated in an atmospheric model; e.g., a general circulation model (GCM). Such a physical approach naturally requires that data for all the relevant variables are available and known within defined accuracy limits. But this is the problem: in the Arctic, most of the relevant variables, such as cloud fraction, cloud microphysical properties, surface albedo and temperature, are poorly validated or have been measured only for limited areas and short periods of time. We have previously used such a physical approach to calculate surface radiative fluxes in the Arctic from the International Satellite Cloud Climatology Project (ISCCP) data set (Schweiger and Key, 1994). Through sensitivity studies we found that few of the input variables are known well enough to achieve a desirable accuracy of 5 Wm^{-2} on a monthly time scale. Although progress leading to an improved physical retrieval has been made, (Francis, 1994, 1995), substantial research and thorough validation are required before reliable algorithms will be available that retrieve surface radiative fluxes at all times and everywhere in the Arctic and that do not require substantial tuning. "Tuning" or making unvalidated assumptions about variables is likely to introduce significant biases. We therefore believe that for the near- to mid-term an empirical approach incorporating physically relevant satellite and surface observations is more promising for delivering accurate, unbiased surface radiation fluxes in the Arctic. In addition, physical retrieval methods commonly impose a significant computational burden since both inverse and forward radiative transfer calculations need to be performed. Performing these calculations for a multiyear data set using radiative transfer models with the required degree of sophistication -- even for a limited area such as the polar regions -- presents a formidable computational task.

3. METHODOLOGY

3.1 What is a neural net?

Artificial neural networks (ANN) were initially used by neuroscientists in an attempt to understand certain functions of the brain. Over the past decade they have increasingly been applied to tasks involving the recognition of complex patterns such as signal processing, optical character recognition, and even stock market forecasting. Although a variety of ANN architectures has been created, the three-layer backpropagation network is the most popular and is currently used in this research. Such networks consist of interconnected units (nodes) that are organized in three layers: an input, an output, and a hidden layer (Figure 1). Information in a neural network is processed by passing activation along connections between individual nodes. This is done by calculating the activation A of node i as the weighted sum of the activations at the connected nodes N:

$$A_i = f\left(\sum_N w_{in} A_n\right) \tag{1}$$

where w_{in} is the weight for the connection between nodes i and n and f is the a nonlinear function called the activation function. Frequently a sigmoid function is used

$$:f(A) = \frac{1}{1 + exp\,(-A)} \tag{2}$$

As the network is presented with an input pattern, activation at the input nodes is propagated over the hidden nodes resulting in a pattern at the output nodes. Initially the weights between individual nodes are random and no information is contained in the network. Adjusting the weights w_{in} for connections between nodes is called the "learning" process. An ANN can be viewed as a vector function O=F(I), where O is the vector of output unit activities and I is the input unit vector. In a backpropagation network, "learning" is achieved simply by finding the weights w_{in} so as to minimize the difference between a presented training pattern and O. This learning cycle involves the repetitive simultaneous presentation of matching input and output patterns while the weights are adjusted using a gradient descent search. Thus a neural network can also be viewed as a non-linear numerical optimization procedure. Neural networks are very attractive for some optimization problems for the following reasons:

- They are suitable for applications that are not easily described analytically, and they can theoretically determine any computable function.
- Except for training patterns no additional information (e.g., partial derivatives) is needed.
- They are suitable for any type of pattern and data type, e.g., integer, real, or binary.
- They are good with the noisy data frequently encountered in geophysics.
- No assumptions about the statistical distribution of input variables are made.
- After training they are extremely fast. They are easily implemented on parallel architectures.

3.2 Why do we expect this to work?

In order for a neural network to generalize over a particular problem rather than just "memorize" each individual case, it has to be presented with the appropriate information to perform this task. Clearly, if there is no general relationship between TOVS brightness temperatures and downwelling radiative fluxes at the surface, the network will not be able to learn this task. Although one may approach this problem by providing an input feature vector that contains many types of possibly related information, it is clearly desirable to first examine the physical principles upon which the network is to operate: the TOVS was designed with the retrieval of temperature and humidity profiles in mind, and several algorithms have been established to invert TOVS sensor radiances. Recent improvements in the 3I algorithms (*Claud et al, 1989; Francis, 1994, 1995*) have demonstrated that TOVS radiances can be used to derive temperature and humidity profiles over more problematic polar surfaces. Francis *(1995)* further demonstrated that a combination of HIRS channels can be used to obtain information on cloud-type and cloud-phase, and to estimate cloud physical thickness and cloud droplet effective radius for certain types of clouds. Recent theory by Nakajima and King (1990), adapted and applied to polar surfaces by Key and Stone (1995), has shown the capability of the AVHRR sensor (TOVS has almost all AVHRR channels) to simultaneously retrieve cloud optical thickness and cloud effective droplet size. In addition, statistical relationships between brightness temperatures and surface radiative fluxes can be exploited by the network. For example, a statistical relationship exists between TOVS MSU channel 2 and observed ice surface temperatures under cloudy skies during winter (Francis, 1994) and can be explained by the "radiation boundary layer" theory of Overland and Guest (1991).

4. Data

Results are presented for two separate time periods and locations: the Coordinated Eastern ARctic Experiment from October 1988 through December 1988 (CEAREX Drift group, 1990) and the LeadEx experiment in the Beaufort Sea from March 24 1992 through April 4 1992 (LeadEx Group, 1993). The CEAREX time period was for the most part during the polar night, so only measurements of downwelling longwave fluxes are available. Measurements were made on a drifting ice camp and the on research vessel *Polarbjøern* using an Eppley pyrgeometer. The data were corrected for dome temperature, and frost and snow were removed manually. Data were averaged over 10 minute intervals. Measurements during the LeadEx period were also made at a drifting ice camp. Short and longwave measurements were made and averaged at 1-hour intervals, also using Eppley instruments. TOVS MSU and HIRS data for these periods were acquired from the National Center of Atmospheric Research (NCAR) and NOAA NESDIS and collocated with the ground measurements. HIRS and MSU brightness temperatures were computed and interpolated to "retrieval boxes" using the corresponding steps of the 3I algorithm (*Chedin et al.*, 1985). To allow a direct comparison with the physical method of Francis (1995), only those data points that were not rejected by the 3I algorithm were used in this study.

5. RESULTS

5.1 Results from CEAREX data set

A 3-layer backpropagation neural network was constructed to learn the relationship between HIRS and MSU brightness temperatures and downwelling longwave radiation in the eastern Canadian Arctic for the period October 1 through December 12, 1988. The input vector consisted of the 19 HIRS and 4 MSU brightness temperatures. The sensor scan angle was included as an additional input node. Observed downwelling longwave fluxes measured at the ice camp and aboard the *Polarbjørn* were used as outputs. The network had a single 2-node intermediate layer. Only those TOVS and surface observation pairs that were within a 100 km radius and within 1 hour from time of observation were selected, yielding a data set of 127 observation pairs. Training (83) and test (34) cases were randomly drawn without replacement from these observations. Upon training, the network was applied to the test data set. Figure 2 shows a comparison of observed and network-derived downwelling longwave fluxes for the test case. Figure 3 shows the same data as a time series along with the results from the physical retrieval method devised by Francis (1995). Figures 2 and 3 demonstrate the good agreement of network-derived fluxes with surface observations. It also demonstrates the superior performance of this method to the physical retrieval method, albeit for a relatively small sample. The mean error for the instantaneous observations in this experiment is 9.7 Wm^{-2} with a standard deviation of 15.48 Wm^{-2}. Even though the mean error for the physical method is slightly smaller than the RADnet retrievals, the scatter in the physical retrieval is larger than for RADnet retrievals. Further analysis is necessary to determine the reasons for several outliers. Given the nature of this comparison (point vs. 100 km average) and the intrinsic error in surface observations of radiation in the Arctic (e.g., frost covering of measurement dome), we consider these results to be very encouraging

5.2 Results from the LEADEX experiment

Measurements in the LEADEX data set represent late spring conditions (March 24, 1992 through April 24, 1992) for a location in the Beaufort Sea. Measurements of downwelling long and shortwave radiation were made at a stationary ice camp. TOVS brightness temperatures were paired with hourly averages of surface observations using the same criteria as for the CEAREX data set. Randomly selected training and test data sets consisted of 128 and 53 cases respectively. A backpropagation network, similar to the one used for the CEAREX data set, was designed. In this experiment we included visible band (0.69 μm) scaled reflectances from the HIRS sensor (channel 20) and the cosine of the solar zenith angle in the input layer. The output layer consisted of surface observations of downwelling short and longwave radiation. A single 4-node intermediate layer was selected. Figures 4a and 4b are scatterplots for network-computed and observed short and longwave fluxes for the test case. Again the results are very encouraging. The mean error for longwave fluxes is - 29 Wm^{-2} with a standard deviation of 28 Wm^{-2}. Shortwave fluxes are overestimated by the network with a mean error of 11 Wm^{2} and a standard deviation of 48 Wm^{-2}. A time series plot (Figure 5) of network-computed and observed downwelling longwave fluxes shows that they track each other well except for some significant deviations in the middle (t=30) and at the end (t=45) of the time series. Future research will address these problems and identify the specific circumstances leading to these unexpected deviations.

TABLE 1. Retrieval Errors

	Training Cases	Test Cases	Downwelling Longwave RMS	Downwelling Longwave Mean	Downwelling Shortwave RMS	Downwelling Shortwave Mean
CEAREX	83	34	18.0	9.7	NA	NA
Physical Model (Cearex)	NA	34	20.51	7.38	NA	NA
LeadEx	128	53	28.34	-2.9	49.54	11.27

6. DISCUSSION

The results presented above are very encouraging and demonstrate the viability of the method. Clearly we are now faced with the challenge to construct a network that performs the retrievals over a the range of surface and atmospheric conditions that will be encountered within the domain of its intended application. We are currently in the process of assembling a much larger data set from multidecadal measurements of surface radiative fluxes made on Russian drifting stations. In order to further improve retrieval results, it is also important to refine the input feature vector. To accomplish this, we need to better understand how the network performs its tasks and which information in the TOVS brightness temperatures is exploited. Analyzing the 112 connections in the presented neural network is obviously a difficult task. A case by case analysis and comparison with physical retrieval methods is needed. Such an examination will help determine if the the network has "learned" any general principles of radiative transfer or if it is simply exploiting statistical relationships between brightness temperatures and downwelling radiative fluxes unique to this data set. This analysis may also aid the further development of physical retrieval methods.

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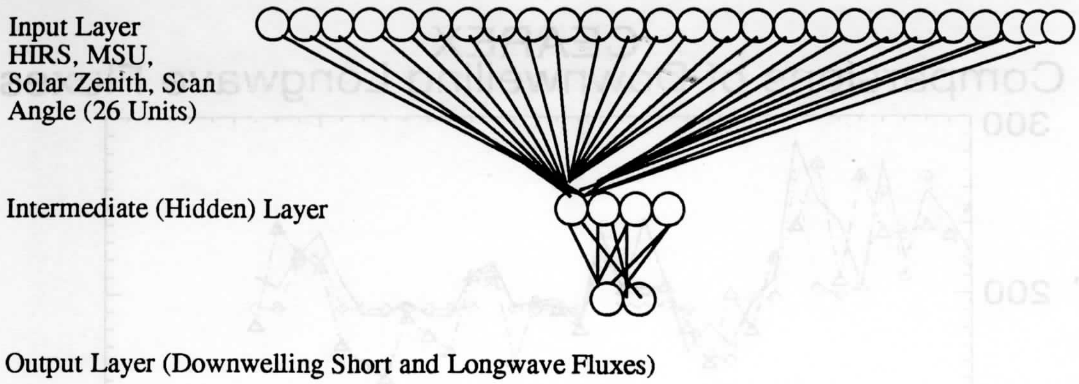

Figure 1. Schematic of network used in the LeadEx Experiment. (Note: Only connections between inputs and first hidden units are shown).

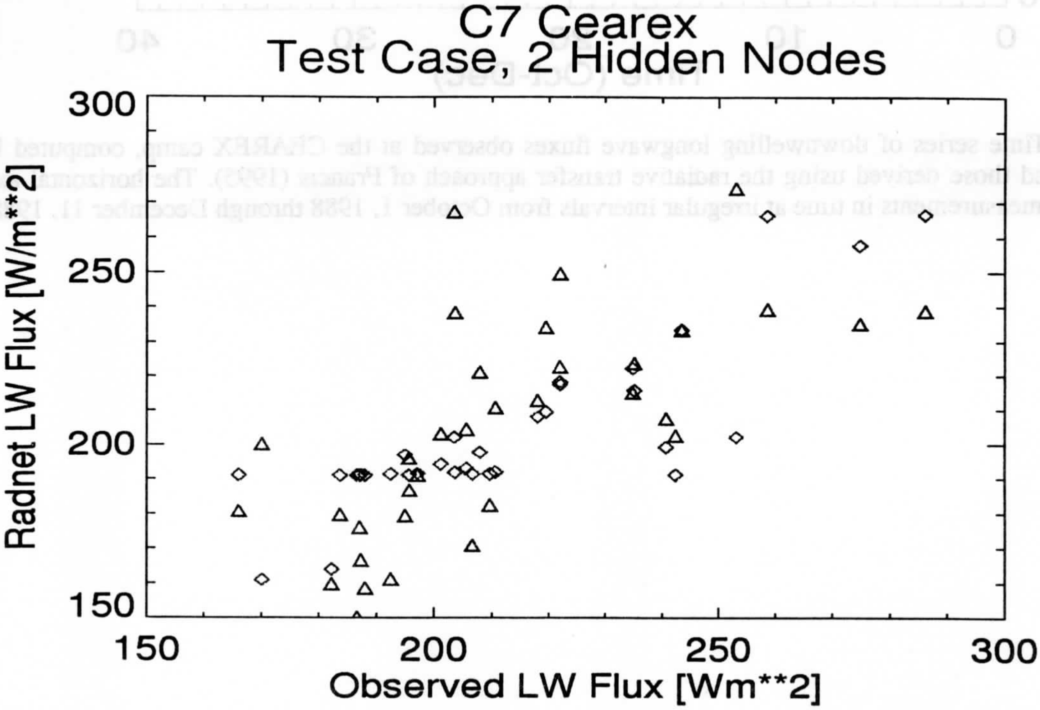

Figure 2. Comparison of downwelling longwave fluxes observed on the surface and computed from TOVS radiances using RADnet (diamonds) and the physical retrieval method of Francis (1995) (triangles) for the CEAREX data set.

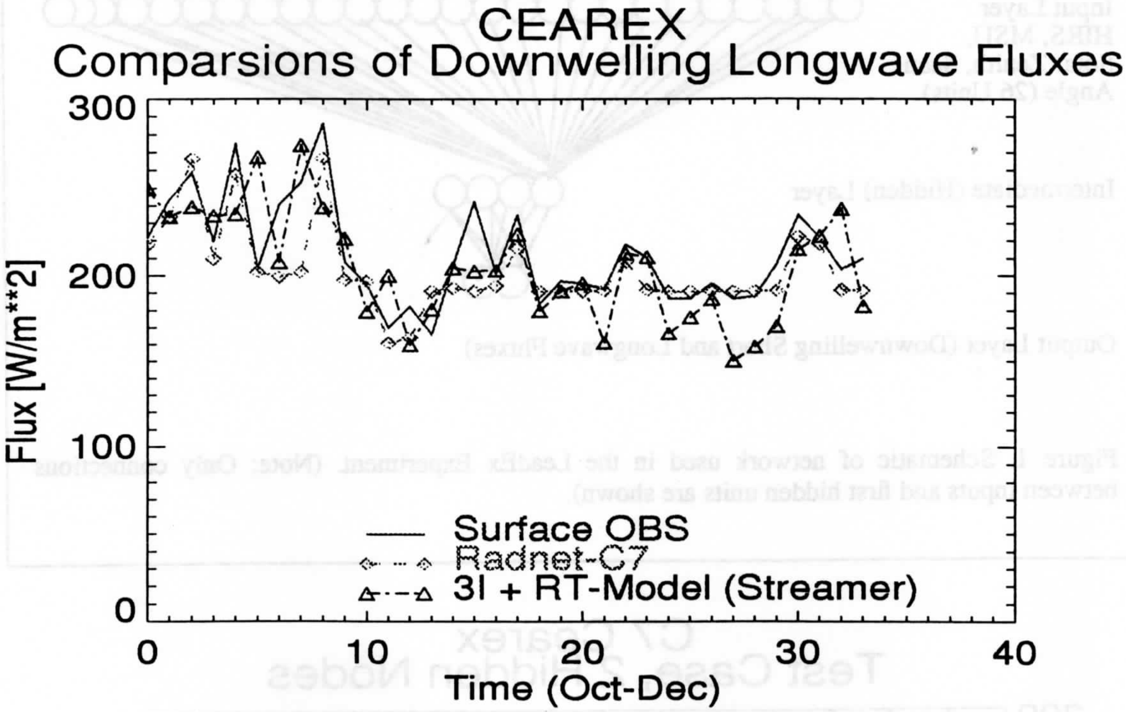

Figure 3. Time series of downwelling longwave fluxes observed at the CEAREX camp, computed by RADnet and those derived using the radiative transfer approach of Francis (1995). The horizontal axis represents measurements in time at irregular intervals from October 1, 1988 through December 11, 1988

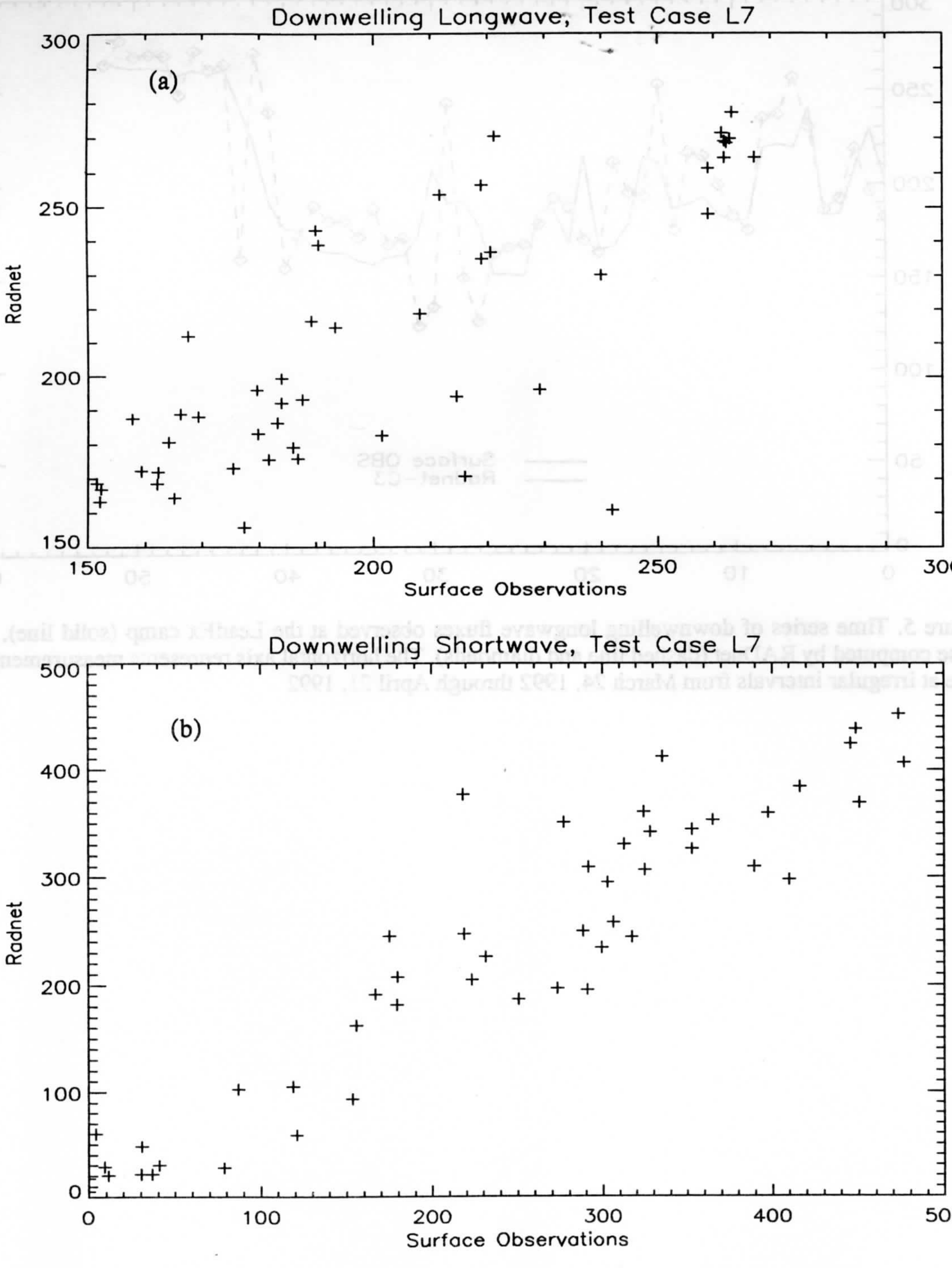

Figure 4. Scatterplots of downwelling longwave (a) and shortwave (b) fluxes observed at the LeadEx camp and those computed by RADnet.

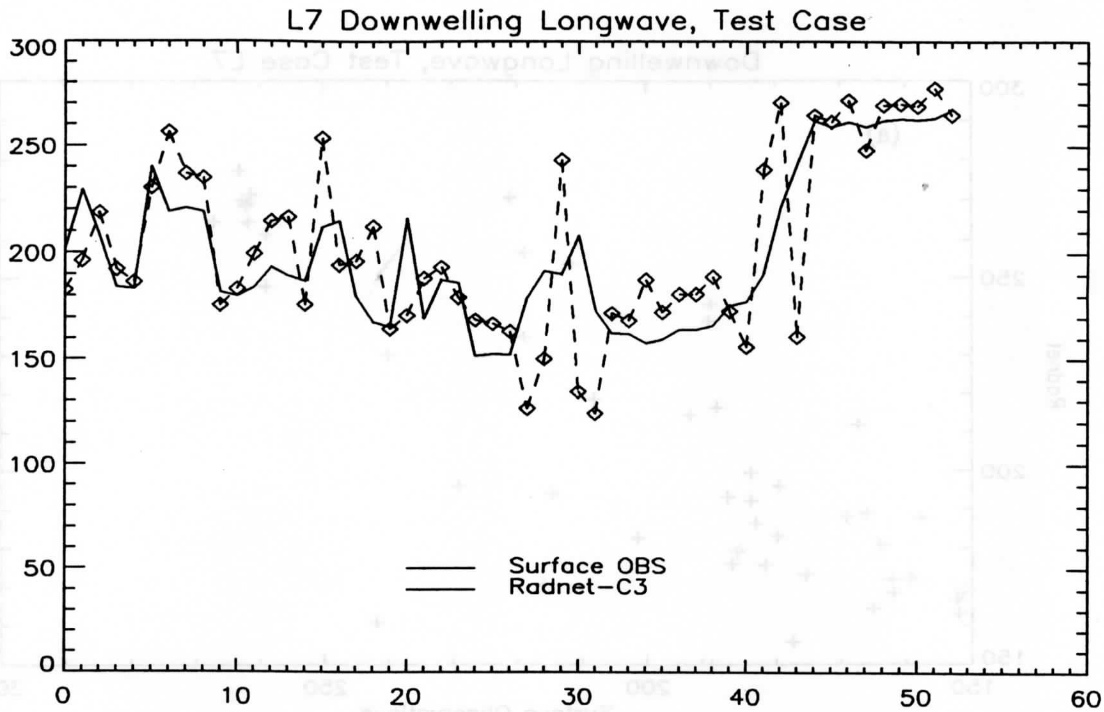

Figure 5. Time series of downwelling longwave fluxes observed at the LeadEx camp (solid line), and those computed by RADnet (dashed line and diamonds). The horizontal axis represents measurements in time at irregular intervals from March 24, 1992 through April 21, 1992

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