Aerosol Size Distribution Using Sun-Photometer and Artificial Neural Network

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Abstract: -Aerosol size distribution (ASD) is an integral parameter in regional atmospheric models [1]. The LIDAR laboratory at UPRM will provide Puerto Rico a means of measuring ASD, and therefore improve these models. This project intends to develop a method of obtaining ASD with the use of a sun-photometer, local CIMEL data obtained from *AERONET* (Aerosol Robotic Network) [2], and an *artificial neural network* (ANN). The sun-photometer used is an instrument that measures *Aerosol Optical Depth* (AOD) on five wavelengths. A feed-forward, back-propagation artificial neural network was used to map the underlying pattern between AOD and ASD in southwestern Puerto Rico. All of the data points available from the La Parguera AERONET station was used for the training of the network, and the ASD predictions by the ANN were very close with small errors in the order of 10^{-4}.

Key-Words: Aerosol Size Distribution, Aerosol Optical Depth, Artificial Neural Network, AERONET

1 Introduction

Puerto Rico has been chosen as a test-bed for the study of hydrological functions of aerosols and cloud formations in the tropical coastal regions. Clouds transport aerosols that drastically affect global weather phenomena. The coastal aerosol boundary typical to tropical coastal areas adds a factor of complexity into the understanding of these cloud dynamics. The major complication is the presence of several types of aerosols such as sea spray, rock debris, sand dust, some anthropogenic in nature, such as smoke from incomplete combustion. In order to study the impact of each type of aerosol on the environment, it is necessary to first be able to tell which aerosols are present at a given moment in a given area. ASD can help experts narrow down the possible types of aerosols present, discriminating by size. ASD can be calculated from LIDAR measurements; this will be one of the main products of the UPRM LIDAR lab. In order to validate the UPRM LIDAR, local ASD will be obtained by an alternate means; this is the focus of this research. The alternate method consists of training an ANN with AOD and ASD data taken at nearby La Parguera by AERONET. If the training data is representative of a consistent pattern between AOD and ASD, the network should produce accurate ASD predictions when presented with an AOD input vector measured at the LIDAR site with our local sun-photometer.

2 ASD determination using Sun-photometer

2.1

2.1 Sun-photometer instrument

The instrument being used to measure AOD at UPRM is a MICROTOPS II portable sun-photometer, pictured in fig. 1. An AOD reading obtained from this instrument consists of a vector of five values, which correspond to five wavelengths: 380, 440, 500, 675, and 870 nm.

The device contains constants of the irradiance measured from the sun in a clean environment (taken at Mauna Loa, Hawaii). The reading is essentially a ratio of the amount of sunlight reaching the device and the constants previously mentioned. One of the drawbacks of the device is the fact that clear skies are necessary in order to take readings. Mayaguez, Puerto Rico is infamous for daily showers, but they tend to happen in the afternoon.

Fig. 1: MICROTOPS II portable SPM

2.2 AERONET database

The Aerosol Robotic Network is a project that provides public access to a global database of several Aerosol-related products, among them, AOD and ASD. Readings are taken daily, but there are many gaps in the data, since, as with the sun-photometer, clear, cloud-free skies are necessary for the instruments to take readings. This detail has proven to be one of the most limiting factors in the accuracy of the ANN predictions. The limitation lies in the fact that the ANN requires an AOD input and an ASD output taken on the same day in order to include that day in its training set. This means a gap in either data set (AOD or ASD) is essentially a gap in both data sets as far as the ANN is concerned. This limitation will become more evident when the ANN training algorithms are discussed. Figs. 2 & 3 contain examples of AERONET AOD and ASD readings, respectively. For the AOD readings, only the 5 wavelengths that are shared with the sun-photometer are taken into account. For the ASD, all 22 points on the plot are used. In order to ensure that the La Parguera AERONET site will generate AOD data similar to that of Mayaguez, an analysis of the spatial variation in AOD between both sites was made [3].

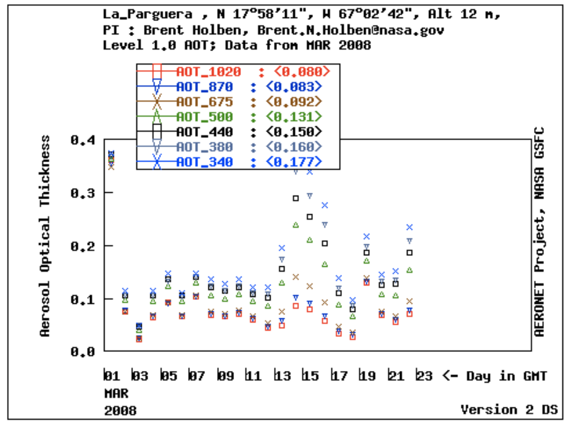

Fig. 2: AERONET AOD plot

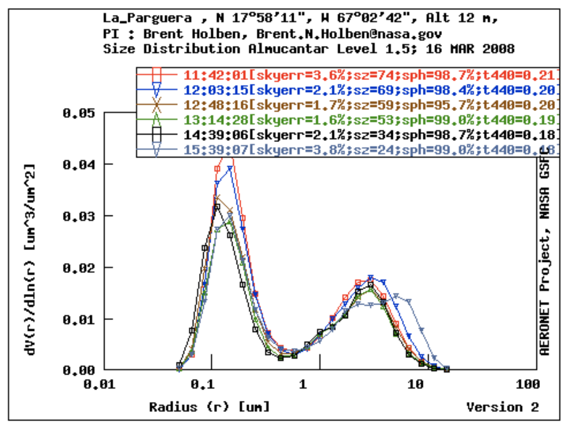

Fig. 3: AERONET ASD plot

2.3 Artificial Neural Network Design

In order to start off with a well-implemented, efficient neural modeling environment, Matlab's Neural Network Toolbox was used to create the network. The artificial neural network used to estimate ASD has an input vector of size five, corresponding to the five wavelengths of an AOD reading. The network contains a hidden layer of 13 neurons, and an output layer of 22 neurons, which correspond to the 22 points on an AERONET ASD plot. The number of neurons in the hidden layer was experimented with. Increasing the number of neurons in the hidden layer improved the training error, but not significantly by any means. The increase also caused the network to take much longer to train, becoming less feasible as more neurons are added. Each layer in a neural network has a transfer function associated with it; the hidden layer has a log-sigmoid transfer function, and the output layer a linear transfer function. A non-linear transfer function was selected for the hidden layer to allow the network to predict a non-linear pattern.

3 ASD Determination

In order to generate training data for the neural network, a data pool is necessary. Each element in the data pool consists of a pair, p(x, y), where x is the average AOD of one day, and y is the size distribution for that day, both provided by AERONET for the same day. In order to make the data provided by AERONET compatible with the ANN software provided by Matlab, a Java parser was written to translate the AERONET data into Matlab matrices that the ANN can interpret. The parser basically takes any AERONET AOD and ASD data that is given to it and finds dates for which valid AOD and ASD readings were taken. It then creates data points (p(x,y) pairs) in the form of an input matrix consisting of AOD readings, and a corresponding target matrix consisting of the ASD readings that complete the data point pairs.

The network was trained with the popular Levenbergh-Mardquat training algorithm [4]. In order to ensure basic network functionality, it was tested with AOD readings that were part of the training set. The ANN performed as expected, consistently producing an ASD that matched the ASD provided by AERONET for the day of the reading used, with an error of epsilon (the smallest numerical value Matlab can represent). Of course, the network is expected to estimate ASD for AOD readings that are not part of the training set. The first attempts at testing the network with unknown AOD inputs was done using the entire data pool as the network's training set. In other words, all the data points available were used for training. In an attempt to find a training set size that minimized network error, training sets were gradually made smaller, and more localized to the testing dates in question, but this procedure only increased network variability and error.

4 Conclusion

When trained with all the data points available from the La Parguera AERONET station, the network was able to converge upon an error of almost 10^{-4}, producing ASD predictions such as those shown in Figs 4, 5 & 6. The network generally produces ASD plots that are a decent match of AERONET ASD plots for that day almost exactly.

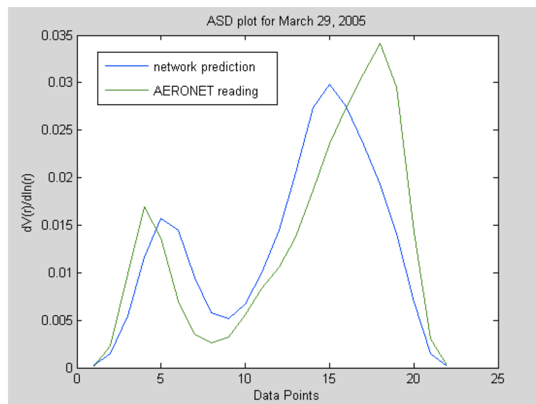

Fig. 4: ASD plot for March 29, 2005, trained with all data points

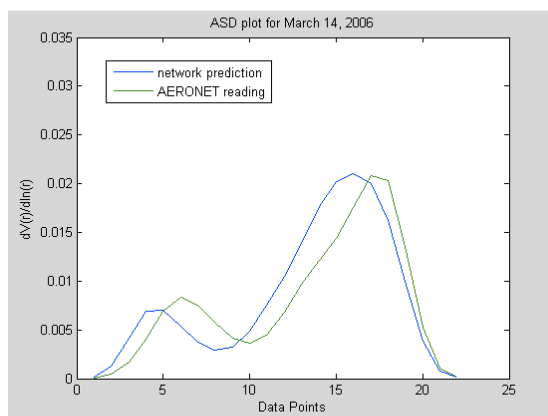

Fig. 5: ASD plot for March 14, 2006, trained with all data points

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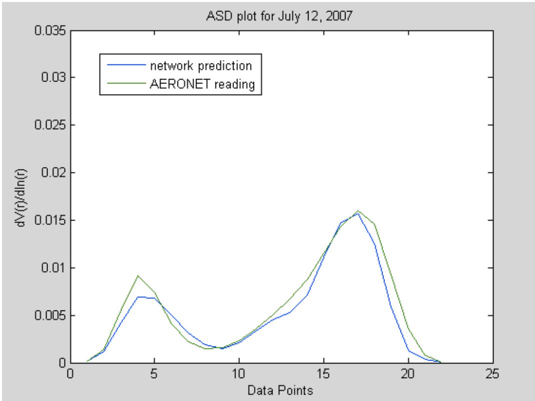

Fig. 6: ASD plot for July 12, 2007, trained with all data points

Several other training sets were experimented with. Specifically, the network was trained with data pertaining to the days preceding the day of the reading being predicted. As the training set became smaller, network performance became less consistent. It made more accurate predictions on some dates, but also made many illogical predictions. The ANN's performance for any given day basically depends on whether or not the training set contains data similar to the day being predicted. If it does, then the prediction will usually be fairly accurate. However, it is impossible to know if the training set contains readings similar to the one being predicted, so limiting the data set to a monthly, weekly, or even seasonal set is out of the question. A network trained with a limited data set can achieve errors of epsilon, but this is misleading, since it is only memorizing the training data, and in a sense, becoming a sort of savant, that is, it only predicts ASD correctly when it is similar to the ASD it was trained with; otherwise, it produces greatly erroneous results.

It is clear from Figs. 4, 5, & 6 that when trained with all the data available from La Parguera, the network makes roughly accurate estimates. However, if the network had more data in its training set, its prediction error could be lowered and it could map the relationship between AOD and ASD more accurately, based on many more data points.

5. Acknowledgements

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