Reduction of Ground-Based Sensor Sites for Spatio-Temporal Analysis of Aerosols

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ABSTRACT

In many remote sensing applications it is important to use multiple sensors to be able to understand the major spatio-temporal distribution patterns of an observed phenomenon. A particular remote sensing application addressed in this study is estimation of an important property of atmosphere, called Aerosol Optical Depth (AOD). Remote sensing data for AOD estimation are collected from ground and satellite-based sensors. Satellite-based measurements can be used as attributes for estimation of AOD and in this way could lead to better understanding of spatio-temporal aerosol patterns on a global scale. Ground-based AOD estimation is more accurate and is traditionally used as ground-truth information in validation of satellite-based AOD estimations. In contrast to this traditional role of ground-based sensors, a data mining approach allows more active use of ground-based measurements as labels in supervised learning of a regression model for AOD estimation from satellite measurements. Considering the high operational costs of ground-based sensors, we are studying a budget-cut scenario that requires a reduction in a number of ground-based sensors. To minimize loss of information, the objective is to retain sensors that are the most useful as a source of labeled data. The proposed goodness criterion for the selection is how close the accuracy of a regression model built on data from a reduced sensor set is to the accuracy of a model built of the entire set of sensors. We developed an iterative method that removes sensors one by one from locations where AOD can be predicted most accurately using training data from the remaining sites. Extensive experiments on two years of globally distributed AERONET ground-based sensor data provide strong evidence that sensors selected using the proposed algorithm are more informative than the competing approaches that select sensors at random or that select sensors based on spatial diversity.

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Categories and Subject Descriptors

J.3 [**Computer Applications**]: Physical Sciences and Engineering – *Earth and atmospheric sciences*.

General Terms

Algorithms, Measurement, Experimentation.

Keywords

Remote Sensing, Data mining, Regression, Active Learning

1. INTRODUCTION

Aerosols, minute particles suspended in the atmosphere originating from natural and man-made sources, have become one of the main topics in climate research studies [8]. They have significant effect on health [14], vegetation, precipitation [17] and global climate [4]. Aerosols were identified as a central component missing from general circulation models (GCMs) that simulate climate changes [10]. After accounting for the aerosol effects, model-simulated climate changes have become more realistic [11] and an agreement between GCMs and real observations has been significantly improved.

The main optical property of aerosols is Aerosol Optical Depth (AOD) [13]. AOD is a measure of the visual or optical thickness of an aerosol layer. The process of predicting AOD using ground [5] or satellite [9] based observations is known as *AOD retrieval*. Ground based observations are mostly obtained by AErosol RObotic NETwork (AERONET) [5] which is a global remote

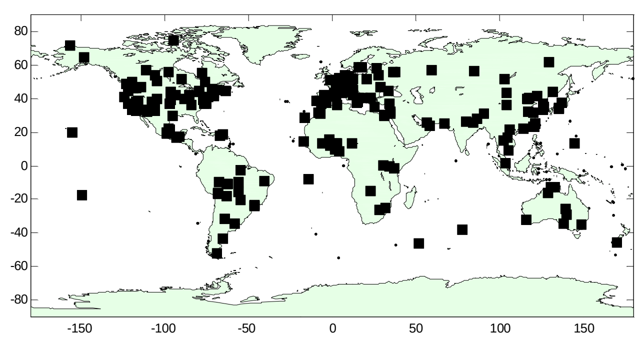


Figure 1. Global distribution of AERONET sites.

sensing network of radiometers that measure AOD several times per hour from specific geographic locations. AERONET instruments provide accurate estimation of local aerosol abundance, but they have low spatial coverage which limits their applicability in understanding global aerosol properties. On the other hand, satellite observations provide global coverage on a daily basis, but are less accurate because the signal that a satellite instrument receives is a mixture of reflected radiation by both the Earth's surface and the aerosol layer [7]. Accuracy of satellite-based AOD retrieval is one of the major limiting factors influencing simulation-based climate change studies [13].

The operational AOD retrieval algorithms are typically manually tuned by domain scientists [16]. While this guarantees that the retrievals are based on sound physical principles, it also creates problems when there is an opportunity to use ground truth data to improve the algorithm. In contrast to domain-driven methods for AOD retrieval that use a network of sensors installed on ground for validation purposes only, a data-driven approach is using them directly to train an algorithm for AOD retrieval from satellite observations. This approach is possible when a data set is available that consists of satellite observations and collocated ground-truth measurements from AERONET radiometers. Given such data, a regression model can be constructed that predicts the ground-truth labels from the satellite observations. In our previous studies to retrieve AOD from satellite observations, a predictor was trained on satellite observations spatially and temporally collocated with AERONET retrievals [18]. It has been shown that such a statistical approach could improve the accuracy of retrievals significantly as compared to the operational domain-based methods. Clearly, this improvement comes from the utilization of highly accurate ground-based measurements directly in the prediction model.

However, ground based stations are often located without a rigorous statistical design. Decisions are typically based on practical circumstances (e.g. overrepresentation in urban regions and industrialized nations) and according to domain experts' assumptions about the importance of specific sites. Furthermore, the total number of sensor sites depends on financial constraints. Costs related to equipment, location, and the availability of trained staff often dictate the number of sites and their global distribution. As shown in Figure 1, AERONET sites are not uniformly distributed over the globe. The highest density is within the U.S. and Europe. On the other hand, continental Asia, Africa, and Australia are poorly covered. Given these circumstances, the aims of our study are to evaluate performance of the current design of AERONET sensor network and to apply data mining techniques to assist in future modifications of the sensor network.

In a tribute to the ongoing economic crisis, a specific scenario considered in this paper assumes that there is a pending budget cut for maintenance of the existing AERONET sites. The objective is to shut down a fraction of the AERONET sites while making sure that the utility of the remaining sites is as high as possible. In this paper, we make a simplifying assumption that operational costs for each AERONET site around the globe are equal.

Common to most selection techniques originating from the spatial statistics is a tendency to overlook the time dimension of data collected by the sensor network. In this paper, for the problem of selecting a subset of data collection sites, we consider series of observations and propose to optimize AERONET sensor selection based on the concept of retrieval accuracy. The intuition behind our proposal is straightforward. Each AERONET site provides a time series which can be used in training a regression model to retrieve future AOD. Sites that can be removed are those whose observations are best predicted by the model built on data from the remaining sites. The performance of the proposed approach is compared with the random site selection and with the classical selection principle of selecting spatially dispersed sites.

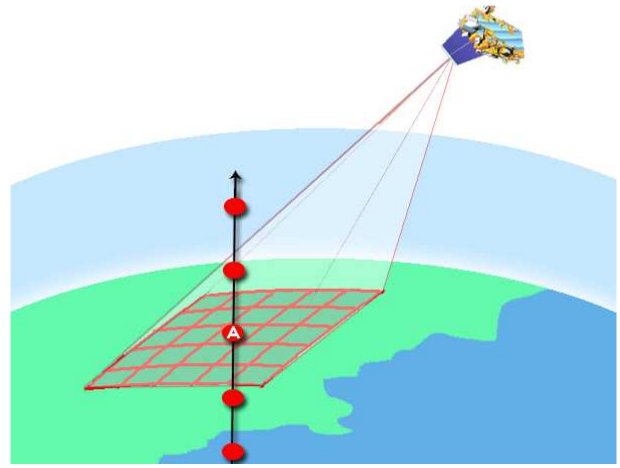


Figure 2. Spatio-temporal collocation of MODIS and AERONET data. A is an AERONET site with AOD retrieved within a short time before and after the satellite overpass (circle dots). The square regions are MODIS observations in a proximity of site A at the satellite overpass time.

2. METHODOLOGY

2.1 Data Fusion

Given a data set that consists of satellite observations and AERONET AOD measurements, a regression model can be trained to use satellite observations as attributes and predict the labels which are AERONET AODs. For that reason, satellite observations need to be collocated and merged with AERONET measurements.

In this study we consider data from MODerate resolution Imaging Spectrometer (MODIS), an instrument aboard NASA's Terra and Aqua satellites. Instruments mounted on Terra observe the Earth during morning whereas those mounted on Aqua observe the Earth during afternoon. In this study, we use data only from Terra satellite.

MODIS has high spatial resolution (pixel is as small as $250x250m^2$) and achieves global coverage daily. On the other hand, AERONET sites, situated at fixed geographical locations, acquire data at intervals of 15 min on average. This gives rise to the need for both spatial and temporal data fusion (Figure 2). The fusion method involves aggregating MODIS pixels into blocks of size 50x50 km^2 and spatially collocating them with an AERONET site. The MODIS observations are said to be temporally collocated with the corresponding AERONET AOD retrievals if there is a valid AERONET AOD retrieval within 30 minutes of the satellite overpass. The data collocated in this way can be obtained from the official MODIS website of NASA [6].

2.2 Regression Model

Let us assume we have access to data from a set of N AERONET sites $S = \{S_i, i = 1, 2, \ldots N\}$. At site S_i there is a sequence $\{(X_{it}, y_{it})\}$ of multivariate radiance observations X_{it} collected from a satellite instrument spatio-temporally collocated with the corresponding ground-based AERONET AOD values y_{it}. To be able to accurately retrieve AOD from MODIS measurements we are using all labeled data from sensor set S to train a regression model f aimed to estimate target AOD values. Typically, the following data-generating model is assumed

$$Y = f(X) + \varepsilon, \varepsilon \sim \mathrm{N}(0, \sigma^2), \quad (1)$$

where ε is Gaussian additive noise with constant variance σ^2.

Neural networks are often a regression model of choice in data-driven retrieval of atmospheric properties [1, 12]. In our previous work, neural networks have been trained to predict AERONET AOD over continental US [3] and whole globe [15] using attributes derived from satellite data. Comparing to the domain-based AOD retrievals, neural network AOD predictions were significantly more accurate.

The assumption of constant variance is a basic requirement in constructing a model. In many cases there is no reason to suspect that the error variance is not constant. However, our inspection of residual plot $f(X) - Y$ as a function of $f(X)$ *provides evidence that this assumption is violated at a certain AERONET sites*. At Figure 3 we notice that in our application variance σ^2 is not constant, but is proportional to $f(X)$.

Variance stabilizing transformations of target variable are often useful in these cases [2]. The strength of transformation depends on its curvature. Square root and logarithmic transformations are popular in practice. In square root transformation, a regression model that predicts $Z = \sqrt{Y}$ is trained and the prediction is provided as $\hat{Y} = \hat{Z}^2$, while in logarithmic transformation Z = log(Y) and $\hat{Y} = \exp(\hat{Z})$. Square transformation is considered as a relatively mild [2] comparing to the logarithmic and is often applied when variance of residuals increases linearly with predicted variable. In the experimental section we compared both of them with the standard approach that does not transform the target variable.

2.3 Selection of Informative AERONET Sites

Let us assume that a mission objective is to close down a fraction (33% or 66% in our experiments) of AERONET sites as to reduce ground-based data collection costs. Given such a budget cut situation, question of our interest is how to select M ($<N$) of the currently available N AERONET sites such that this subset captures as much information as possible compared to the entire set S. The goodness criterion for a selection is accuracy of a regression model built on labeled data from the retained sites.

Intuitively, it appears that the selection of sites that are spatially dispersed would be a better choice than a random elimination. Such a spatial selection might be aided by domain experts — they would prefer to keep representative sites around the globe that cover a variety of meteorological and environmental conditions. However, regardless of the experts' effort, spatial representatives selected this way may not be optimal with respect to the quality of the resulting regression model f.

Table 1. List of attributes collected from the collocated satellite observations

Attribute index	Description
1-4	Mean radiation in 50 x 50 km^2 blocks at seven wavelengths
5-9	Std. deviation of radiation in 50 x 50 km^2 blocks at seven wavelengths
10-13	Ancillary attributes (view angles, elevation)

The sites selected by a domain expert are likely to be spatially diverse. To approximate the decision-making process of domain experts, for benchmarking purposes we use the spatial selection strategy based on spatial distance among sites. In the first step two sites that are closest to each other are determined. One of them whose removal better preserves global coverage is excluded from the set S. To decide which one is going to be removed, we are consulting the nearest neighbors of those two sites. The site which has the closer second nearest neighbor is removed. This procedure is iteratively repeated until the desired number of M sites is reached.

Our proposed strategy for selection of M sites out of N is accuracy-based. At the first step, the regression model f is trained on the data from the entire set of AERONET sites. At successive steps, every location is taken out and a model is built on data from the remaining sites. By $\hat{Y}$ we denote AOD retrieval obtained by a model trained on whole dataset and by $\hat{Y}^{(i)}$ AOD retrieval obtained by a model trained on $S \backslash S_i$ sites that exclude examples from site S_i. The intuition is that if AODs from site S_i can be estimated with a model which has not seen that site, then site S_i can be considered as redundant and therefore can be removed. To quantitatively define redundancy, we measure the difference in AOD retrieval accuracy between the model trained on the whole dataset and model trained on a dataset without examples from site S_i. The difference in retrieval accuracy is measured at data from site S_i as a sum of squared differences in retrieved AODs computed over all points from site S_i

$$SSE_i = \sum_t (\hat{y}_i - \hat{y}_t^{(i)})^2 \quad (2)$$

A site that is removed is the one with the smallest SSE as its AOD is the easiest to estimate given data from the remaining sites. Once a site is removed the proposed procedure is repeated. It continues by comparing the reduced models to the model built on the entire data, where data from the most recently excluded site are used for calculating SSE based loss.

3. EXPERIMENTAL RESULTS

3.1 Dataset

There are several levels of AERONET AOD measurements [5]. To avoid potential problems with outliers in ground truth data, AERONET Level 2.0 observations were considered since they were cloud screened and manually verified.

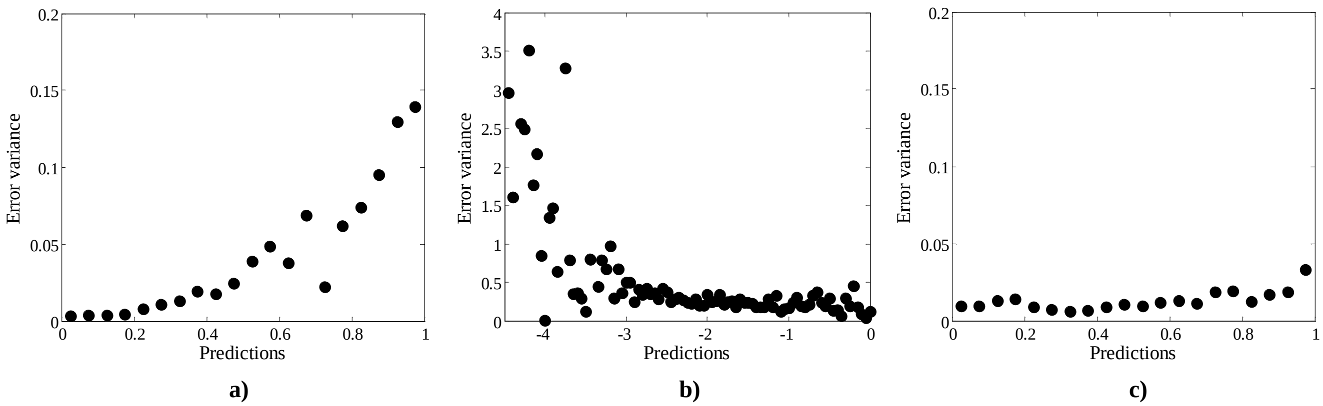


Figure 3. Variance stabilizing effect of square root transformation. Error variance as a function of a) predictions without transformation b) predictions with log transformation c) predictions with square root transformation

Table 2. R^2 statistics on 2006 data for neural network models without (*NN*) and with log (*NNLG*) or square root (*NNSQ*) transformed output each built on ten different sets of 30 randomly selected sites using 2005 data.

Model	***R^2***				
	Mean	Std	Median	Min	Max
NN	0.659	0.086	0.671	0.459	0.742
NNLG	0.664	0.091	0.703	0.444	0.721
NNSQ	0.746	0.042	0.754	0.644	0.789

For our study we collected MODIS Terra observations collocated with AERONET Level 2.0 points. We extracted satellite-based attributes that are used as inputs to knowledge based retrieval algorithms. The radiances at four wavelengths were taken from the MODIS range 440nm – 2100nm, as these are sufficient to describe aerosol properties [16]. An average and standard deviation of radiances of pixels in 50x50 km^2 blocks were then estimated. Attributes are listed in Table 1. Along with radiances we also extracted ancillary attributes. Information about geometry is characterized by solar and sensor angles. As surface elevation affects estimated AOD, it was also included in the set of attributes and has been extracted from AERONET data.

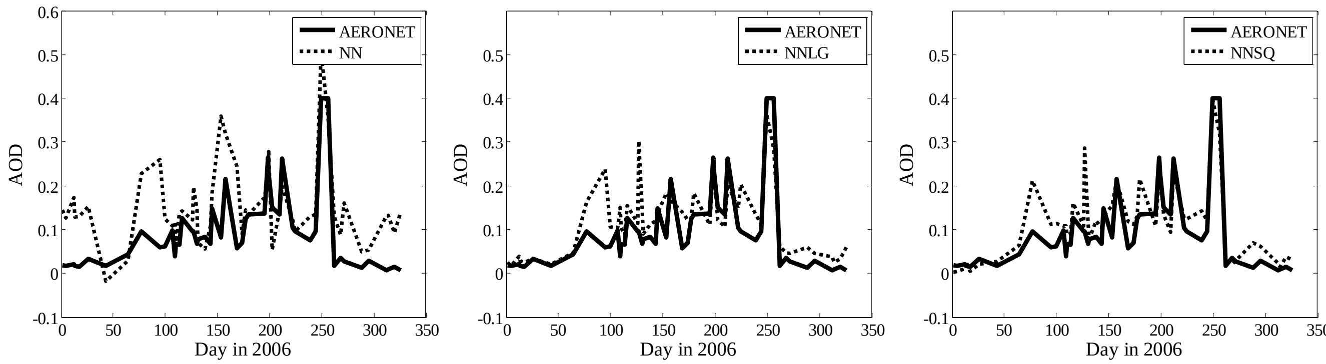
By convention, AOD is reported at the 550nm wavelength. Since AERONET sites do not provide AOD value at that particular wavelength, we performed a standard linear interpolation in the log scale of AERONET AOD measurements at 440nm and 670nm to estimate AOD at 550nm [16].

Data we collected are distributed over entire globe at 217 AERONET sites (Figure 1) during years 2005 and 2006. To assess efficiency of the proposed methods, we performed training on 2005 data and used 2006 data for testing. However, during that time period measurements from AERONET sites were not uniformly distributed, neither temporally or spatially. There were many more points from June to August than from January to May. Also, at some cloudy locations it was not possible to measure AOD and those locations contained a small number of data points. To maintain uniformity of the training dataset, in each training session we randomly selected 30 sites in year 2005 as the initial set *S*. Only 70 randomly chosen observations from each of those AERONET site were retained and remaining ones were removed. Finally, the training set consisted of 2,100 data points distributed over 30 AERONET sites each containing 70 collocated observations. As the test set, we randomly sampled 50 points from each site in 2006. Sites with less than 50 valid observations were excluded. The constructed test set contained 3,500 data points distributed over 70 AERONET sites each having 50 collocated observations. It is worth mentioning that among 70 test sites, 30 were the same as in the training set, while 40 sites were not seen during training. To evaluate the proposed approach, we report R^2 accuracy on the test set.

3.2 Determining an Appropriate AOD Transformation

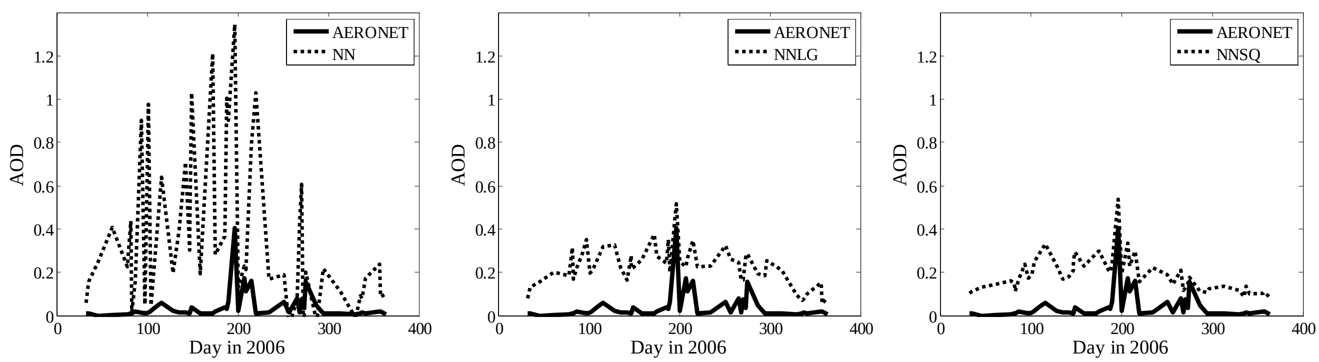
To validate the assumption that error variance is not constant and that empirically selected square root transformation is the most appropriate one, we performed the following experiment. Thirty sites in 2005 were chosen randomly. Three regression models, one with data preprocessed by the square root transformation (*NNSQ*), one with data preprocessed by the log transformation (*NNLG*) and the other without the transformation (*NN*), were trained on the selected dataset and compared on the test set. As a regression model we used a neural network with ten hidden neurons trained to optimize standard Mean Square Error (*MSE*) function.

This procedure was repeated ten times for different sets of 30 randomly selected sites. We report R^2 accuracy achieved on the fixed test set covering the 70 sites during 2006. To estimate sensitivity of constructed models to distribution of the initial 30 sites, we report mean, standard deviation, median and minimum and maximum of R^2 in those ten iterations. The results are presented in Table 2. These results provide strong evidence that the neural networks trained to predict AOD squared root (*NNSQ*) are more accurate than those trained to predict raw AOD (*NN*) or log-AOD (*NNLG*). Additionally, the presented results reveal that retrieval accuracy is sensitive to the choice of the initial set of *S* sites. Although each time the selected 30 sites were globally distributed covering all parts of the world, in some cases accuracy dropped significantly. A possible explanation could be that some of those sites have noisy data that negatively influence model performance.



a) **b)** **c)**

Figure 4. AERONET AOD at site ‘BSRN_BAO_Boulder’, along with AOD retrievals by a) *NN*, b) *NNLG* and c) *NNSQ* models built on data from 30 sites



a) **b)** **c)**

Figure 5. AERONET AOD at site ‘Izana’, along with AOD retrievals by a) *NN*, b) *NNLG* and c) *NNSQ* models built on data from 30 sites

To better illustrate the effect of the square root transformation, at Figure 3 we show variance of prediction errors as a function of predictions. As can be seen, if the transformation is not used, the error variance is large when large AODs are predicted. On the other hand, when the strong log-transformation is used, the error variance is large when small AODs are predicted. Finally, when square root transformation is used, error variance is practically constant and does not depend on the value of predicted AOD. Thus, minimizing MSE assuming constant variance (as in (1)) is justified for the square-root transformed AOD.

To get better insight how transformations influence prediction accuracy, we analyzed a series of AOD retrievals at AERONET site ‘BSRN_BAO_Boulder’ (40ºN, -105ºW). Sensor platform is on the rooftop of the building which is located on the high plains about 15 miles east of Boulder, CO, USA. Surrounding farmers’ fields make satellite AOD retrieval easier in some yearly seasons. Satellite retrievals are more accurate over green regions which are often considered as dark [16] and therefore do not have an influence on observed radiation. AOD data from this AERONET site along with AOD retrievals of *NN*, *NNLG* and *NNSQ* are presented in Figure 4a, 4b and 4c respectively. By visual inspection of those plots we can see that if AERONET instrument from this site measures small AOD then model *NN* retrieves large AOD whereas both *NNLG* and *NNSQ* manage to retrieve small AOD. Although it looks that *NNLG* and *NNSQ* achieve similar accuracy comparing to AERONET AOD, by inspecting R^2 which is 0.72 for *NNSQ*, 0.54 for *NNLG* and -0.1 for *NN* we conclude that *NNSQ* is more accurate than *NNLG* and *NN*.

To explore how the proposed square root transformation influences prediction accuracy at some extreme situations we analyzed AOD predictions of the least accurate *NN*, *NNLG* and *NNSQ* neural networks. We observed that the largest retrieval errors were made on the site ‘Izana’ (28.3ºN, -16.5ºW) which is located on the island of Tenerife, Spain, at elevation of 2360m above sea level. The sensor platform is placed on the top of a mountain plateau. The sky is usually free of clouds and as a result is extremely clean and suitable for radiation measurements and calibrations. AOD data from this AERONET site along with AOD retrievals of *NN*, *NNLG* and *NNSQ* are presented in Figure 5a, 5b and 5c respectively. We can see that AERONET instrument from this site most of the time measures small AOD while all three models *NN*, *NNLG* and *NNSQ* predict large AOD. However, models *NNLG* and *NNSQ* trained on transformed data manage to make smaller predictions than *NN*.

Based on these results, we used *NNSQ* predictor in the following experiments.

3.3 Selection of Informative Sites

We are considering a scenario when current operational AERONET sites have to be reduced by 33% or 66%. In all experiments, we started from a set of 30 AERONET sites and applied the proposed method and the two alternatives (spatial and random selection) to identify a subset of 20 or 10 AERONET sites to be retained. The *NNSQ* models were trained on labeled data from 2005. To test the goodness of the identified subset we tested the *NNSQ* models on 70 sites from 2006 (as described in Section 3.1).

The R^2 results averaged over 10 repetitions are presented in Figure 6. We noticed that in some cases R^2 drops significantly when spatial and random selection strategies are used. Therefore, we also report median values of R^2 after 10 repetitions (Figure 7). In our experiments, the proposed accuracy-based selection achieved consistently better results than the alternatives. Also, accuracy of the proposed site reduction method did not change much even after removing 20 of the 30 AERONET sites. Interestingly, on average, the spatial selection strategy performed slightly worse than the random selection strategy.

Let us now consider the effect of the proposed sites reduction method on predictions at the site 'BSRN_BAO_Boulder' analyzed previously (Figure 4). Time series of AOD retrievals at this site for a single placement of 30 training sites are presented in Figure 8. *NNSQ* model trained on a reduced dataset was able to retrieve ground-truth AOD slightly less accurately than the model trained on data from all 30 sites. In terms of R^2 accuracy, *NNSQ* trained on a reduced dataset achieved R^2 = 0.64 while *NNSQ* trained on non-reduced dataset achieved R^2 = 0.72 at the site 'BSRN_BAO_Boulder'. The conclusion is that accuracy-based reduction retains most of the accuracy of the model built on non-reduced dataset.

In Figure 9 we illustrate site reduction for one initial placement of 30 AERONET sites. Spatial-based selection of AERONET sites nicely covers whole globe but it is not necessarily optimal for data-driven AOD retrieval problem as we already noticed (Figure 6). On the other hand, some regions of the world were underrepresented when an accuracy-based principle was applied (Figure 9e). The accuracy was retained to a certain extent although no site from East US or from middle Asia was selected.

4. DISCUSSION

In this work we presented a method for the reduction of a number of AERONET sites such that the remaining sites are as informative as possible. The goodness criterion for a site selection is the accuracy of a regression model built on the labeled data from the selected sites. We analyzed three different approaches for site selection. A common-sense approach used as a benchmark was a random selection of sites. An approach based on spatial distance among the sites was also considered. Sites were selected such that their spatial coverage was maximized. As an alternative that takes into account the actual measurements from ground-

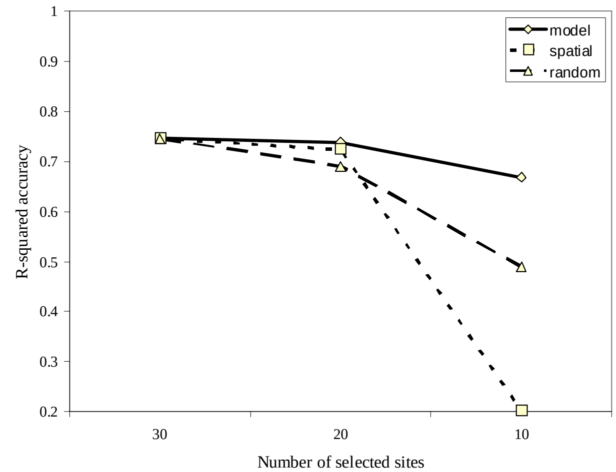


Figure 6. <u>Mean</u> R^2 values in ten iterations for different initial sets of 30 AERONET sites.

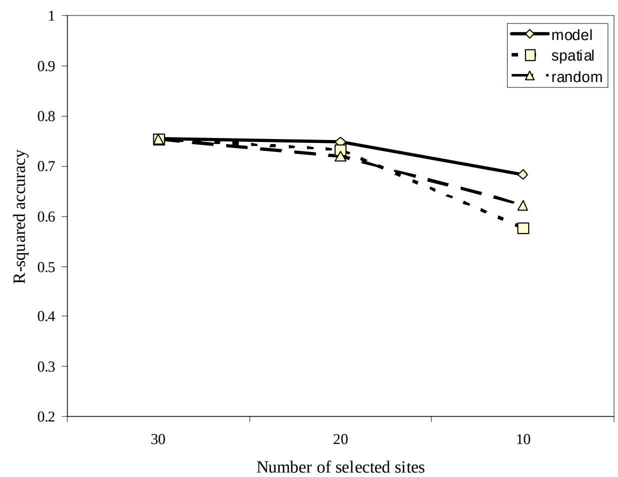


Figure 7. <u>Median</u> R^2 values in ten iterations for different initial sets of 30 AERONET sites.

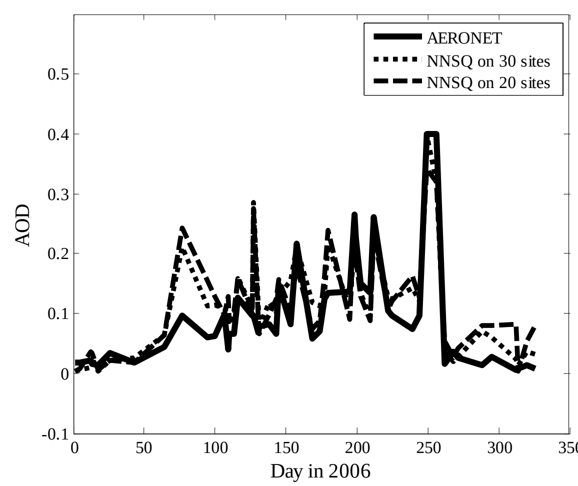
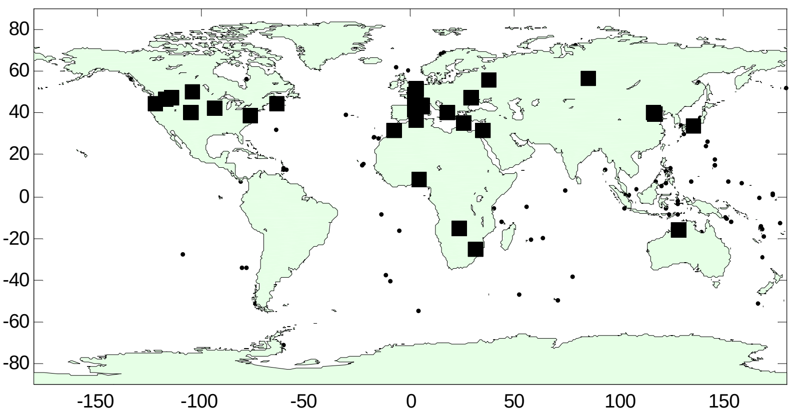
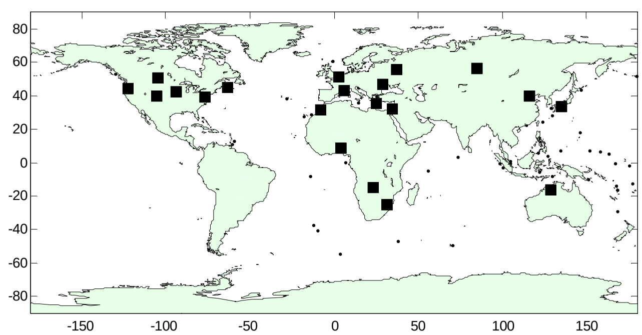


Figure 8. AOD retrievals at site 'BSRN_BAO_Boulder' by *NNSQ* models trained on entire and reduced dataset.



a)



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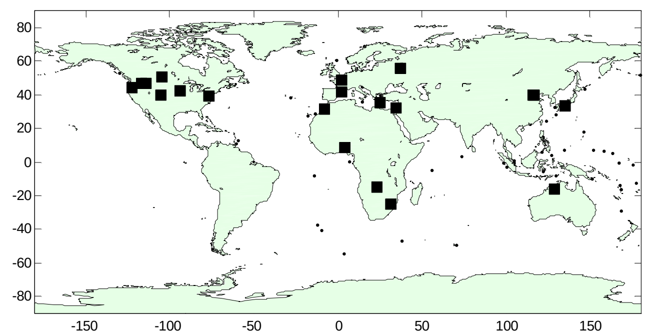

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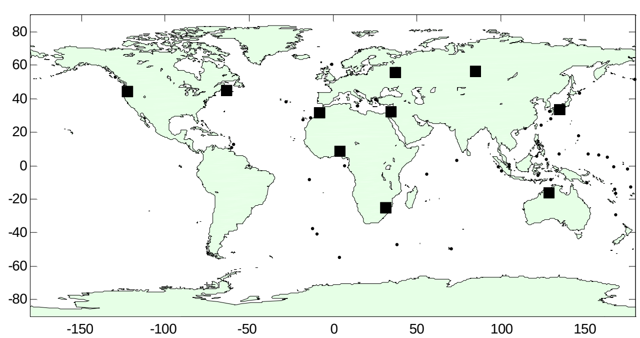

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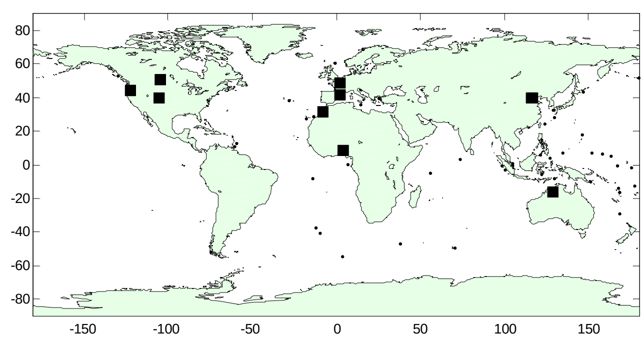

e)

Figure 9. a) Initial set of 30 AERONET sites b) spatial-based reduction to 20 sites c) accuracy-based reduction to 20 sites d) spatial-based reduction to 10 sites e) accuracy-based reduction to 10 sites.

based AERONET sensors and satellite-based MODIS instruments, we proposed an accuracy-based selection approach. For this, a regression model was first trained on the labeled data from an entire set of sensors. After that, at successive steps, every location is excluded to check if AOD from that location can be predicted accurately by the model trained on labeled data from the remaining sites. The intuition was that if AODs from that site can be retrieved fairly well with a model which has not seen that site, then the ground-based measurements at that site can be considered as redundant.

According to presented results we conclude that the proposed accuracy-based sites reduction method is superior to spatially-based and random selection alternatives. In this report we did not address the question of determining the optimal number of sites to reduce the entire set in order to maintain a desired accuracy. This problem is addressed in our work in progress.

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5. REFERENCES

[1] Aires, F., Prigent, C., Rossow, W. B., and Rothstein, M., 2001. A New Neural Network Approach Including First Guess for Retrieval of Atmospheric Watervapor, Cloud Liquid Water Path, Surface Temperature, and Emissivities Overland from Satellite Microwave Observations, J. Geophys. Res., 106, 14,887–14,908

[2] Box, George E. P.; Cox, D. R., 1964. An Analysis of Transformations, Journal of the Royal Statistical Society, Series B 26: 211–246.

[3] Han, B., Vucetic, S., Braverman, A., Obradovic, Z., 2006. A Statistical Complement to Deterministic Algorithms for the Retrieval of Aerosol Optical Thickness from Radiance Data, Engineering Applications of Artificial Intelligence, Vol. 19, No. 7, pp. 787-795.

[4] Hansen, J., Sato, M., and Ruedy, R., 1997. Radiative Forcing and Climate Response, J. Geophys. Res. 102, 6831-6864.

[5] Holben, B. N., Eck, T. F., Slutsker, I., Tanre, T., Buis, J. P., Setzer, A., Vermote, E., Reagan, J. A., Kaufman, Y. J., Nakajima, T., Lavenu, F., Jankowiak, I., and Smirnov, A., 1998. AERONET: A Federated Instrument Network and Data Archive for Aerosol Characterization, Remote Sens. Environ., 37, 2403 – 2412.

[6] http://modis.gsfc.nasa.gov/, Official MODIS website

[7] Kaufman, Y. J., Tanré, D., et al., 1997. Operational Remote Sensing of Tropospheric Aerosol Over Land From EOS Moderate Resolution Imaging Spectroradiometer", Journal of Geophysical Research - Atmospheres 102(D14): 17051-17067.

[8] Kaufman, Y. J., Tanre, D., and Boucher, O., 2002. A Satellite View of Aerosols in the Climate System, Nature, 419, (September 2002), 215-223.

[9] King, M. D., Kaufman, Y. J., Tanré, D., and Nakajima, T., 1999. Remote Sensing of Tropospheric Aerosols from Space: Past, Present, and Future, Bull. Amer. Meteor. Soc., 80, 2229-2259.

[10] Li, Z., 2004. Aerosol and Climate: A Perspective from East Asia, Observation, Theory and Modeling of Atmospheric Variability, (ed. Zhu), World Scientific Pub. Co., 501-525.

[11] Mitchell, J. F. B., Johns, T.C., Gregory, J.M., and Tett, S. F. B., 1995. Climate Response to Increasing Levels of Greenhouse Gases and Sulphate Aerosols, Nature, 376, 501-504.

[12] Muller, M. D., Kaifel, A. K., Weber, M., Tellmann, S., Burrows, J. P., and Loyola, D., 2003. Ozone profileretrieval from Global Ozone Monitoring Experiment (GOME) Data Using a Neural Network Approach (Neural Network Ozone Retrieval System (NNORSY)), J. Geophys. Res., 108(D16), 4497.

[13] Penner, J.E., et al., 2001. Aerosols, their Direct and Indirect Effects, Chapter 5 in Climate Change 2001, The Scientific Basis, Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), Cambridge University Press, 289-348.

[14] Pope, A. C., et al., 2002. Lung Cancer, Cardiopulmonary Mortality, and Long-term Exposure to Fine Particulate Air Pollution", J. Amer. Med. Assoc. 287: 1132-1141

[15] Radosavljevic, V., Vucetic, S., Obradovic, Z., 2008. Spatio-Temporal Partitioning for Improving Aerosol Prediction Accuracy, In Proceedings of the SIAM International Conference on Data Mining, SDM2008, pp. 609-620.

[16] Remer, L. A., Tanré, D., and Kaufman, Y. J., 2006. Algorithm for Remote Sensing of Tropospheric Aerosol from MODIS for Collection 005", http://modis-atmos.gsfc.nasa.gov/atbd02.pdf

[17] Rosenfeld, D., and Woodley, W., 2001. Pollution and Clouds, Physics World, 33-37.

[18] Vucetic, S., Han, B., Mi, W., Li, Z., Obradovic, Z., 2008. A Data Mining Approach for the Validation of Aerosol Retrievals, IEEE Geoscience and Remote Sensing Letters, Vol. 5 (1), 113-117.