Using NNs to Retrieve Multiple Geophysical Parameters from Satellite Data

Vladimir Krasnopolsky, SAIC/GSC, kvladimir@ncep.noaa.gov

Abstract

A new approach in satellite retrievals, multi-parameter empirical retrievals, is introduced. It is shown that single-parameter retrievals, compared with multi-parameter retrievals, contain significant additional "artificial" systematic and random errors. These errors may be avoided using multi-parameter retrieval algorithms. NNs are well suited for developing such multi-parameter retrieval algorithms. The NN approach for developing empirical multi-parameter algorithms is discussed. A new NN empirical algorithm (OMBNN3) which simultaneously retrieves four geophysical parameters: surface wind speed (W), columnar water vapor (V), columnar liquid water (L), and sea surface temperature (SST) T_S from five SSM/I (Special Sensor Microwave Imager) brightness temperatures (BTs) (T19V, T19H, T22V, T37V, and T37H) is presented and compared with several single-parameter algorithms to illustrate advantages of the multi-parameter approach.

Deriving geophysical parameters from satellite measurements

Satellite remote sensing data are used in numerical weather prediction (NWP), field meteorology, fisheries, Coast Guard, the oil industry, the Navy and others. Users work with geophysical parameters such as pressure, temperature, wind speed and direction, water vapor, etc. Satellite sensors generate measurements in terms of radiances, backscatter coefficients, BTs, etc. Satellite retrieval algorithms which transform satellite measurements into geophysical parameters play the role of mediator between satellite measurements and users.

Conventional methods for using satellite data involve solving an inverse (or retrieval) problem and deriving a transfer function (TF), f, which relates a single geophysical parameter of interest, g_i (e.g., surface wind speed over the ocean), to a vector of satellite measurement, s (e.g., SSM/I BTs),

$$g_i = f(s) \qquad (1)$$

The TF, f, may be derived explicitly or assumed implicitly. A single-parameter retrieval algorithm is a particular representation of the transfer function (1).

Usually satellite measurements, s, contain information on several related geophysical parameters. Therefore, in principle, under favorable conditions, these parameters can be retrieved simultaneously from the vector s,

$$G = F(s) \qquad (2)$$

where $G = \{G_i\}_{i=0,1,\ldots}$ is a vector of multiple geophysically related parameters. A multi-parameter retrieval algorithm is a particular representation of the transfer function (2).

Single-parameter retrieval algorithms (1) produce retrievals (e.g., g_k) which do not correspond to any particular atmospheric state or ocean surface state. These retrievals correspond to some unknown "mean" atmospheric and surface states which can not be specified without additional information. Thus, single-parameter retrieval algorithms effectively average over an ensemble of atmospheric and surface states for all of the related geophysical parameters except for the one which is retrieved. This averaging gives rise to additional "artificial" errors in this single retrieved parameter which do not arise in the multi-parameter approach. If g_k is a geophysical parameter retrieved by a single-parameter algorithm (1) and G_k is the same parameter retrieved by the corresponding multi-parameter algorithm (2), then this "artificial" systematic error (bias) can be estimated as,

$$\overline{(G_k - g_k)} = \sum_i \alpha_i b_i + \sum_i \beta_i \sigma_i^2 + \sum_{i,j} \gamma_{ij} c_{ij} + \ldots \qquad (3)$$

The horizontal bar above the symbols on the left-hand side implies averaging over G_i ($i \neq k$) which are not known for single-parameter algorithms, b_i and σ_i^2 are the biases and variances of these geophysical parameters, and the c_{ij} are correlation coefficients between these parameters; α_i, β_i, and γ_{ij} are coefficients which are described in [1]. Similar estimates can be obtained for additional "artificial" variances (random errors). It is clear from (3) that the multi-parameter retrievals, G_k, compared with single-parameter retrievals, g_k, do not contain additional "artificial" systematic (bias) or random errors. Avoiding these additional errors is an important advantage of the multi-parameter approach.

NNs for Multi-Parameter Retrievals

The above considerations show that both single- (1) and multi-parameter (2) retrieval algorithms can be considered as continuous mappings which map a vector of sensor measurements, $s \in \Re^n$, to a vector of geophysical parameters, $G \in \Re^m$. In the case of empirical algorithms, these mappings are constructed, using discrete sets of collocated vectors s and G (matchup data sets $\{s_i, G_i\}$). Single-parameter algorithms (1) may be considered as degenerate mappings where a vector is mapped onto a scalar (or a vector space onto a line).

Linear and nonlinear regressions are standard tools that can be used to develop single-parameter retrieval algorithms (to model TF). If TF is nonlinear, the linear regression can give only a local approximation, or, if it is applied globally, this approximation usually has poor accuracy. Nonlinear regression is usually better suited for modeling TFs. However, in this case, we need to introduce a particular kind of nonlinearity in advance, which we use to approximate the TF under consideration. This may not always be possible, because we may not know in advance what kind of nonlinear behavior a particular TF demonstrates, or this nonlinear behavior may be different in different regions of the TF's domain. If an incorrect nonlinear regression is chosen (by chance), it may represent a nonlinear TF with less accuracy than a linear regression. Regressions can also be used for multi-parameter retrievals; however, from a calculational point of view, this problem is nonstandard.

In the situation described above, where we do know that the TF is nonlinear but do not know what kind of nonlinearity to expect, and where multi-parameter retrievals are desirable, we need a flexible, self-adjustable approach that can accommodate various types of nonlinear behavior, represent a broad class of nonlinear mappings, and one that can be easily used for both single- and multi-parameter retrievals. Neural networks (NNs) are well suited for a very broad class of nonlinear approximations and mappings. It has been shown [2] that a NN with one hidden layer can approximate any continuous mapping defined on compact sets in $\Re^n$. Thus, any retrieval problem which can be mathematically reduced to a nonlinear mapping like (1) or (2) can be solved using a NN with one hidden layer.

A SSM/I Empirical Multi-Parameter Retrieval Algorithm: OMBNN3

As an example of the approach described above, here we introduce a multi-parameter empirical algorithm (2) which has been developed [3] to retrieve a vector of geophysical parameters $G = \{W, V, L, T_S\}$ from five SSM/I BTs (T19V, T19H, T22V, T37V, and T37H). These parameters are surface wind speed (W), columnar water vapor (V), columnar liquid water (L), and sea surface temperature (SST) T_S. Fig. 1 shows the architecture of a simple feedforward NN with one hidden layer which implements the OMBNN3 algorithm.

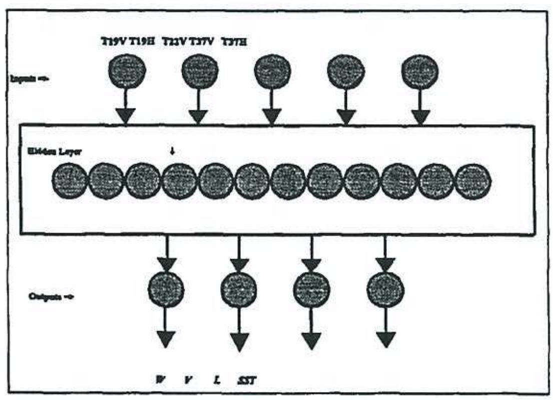


Fig.1.OMBNN3 architecture.

This NN has $n = 5$ inputs, $m = 4$ outputs, and one hidden layer with $k = 12$ neurons. This NN can also be written explicitly as,

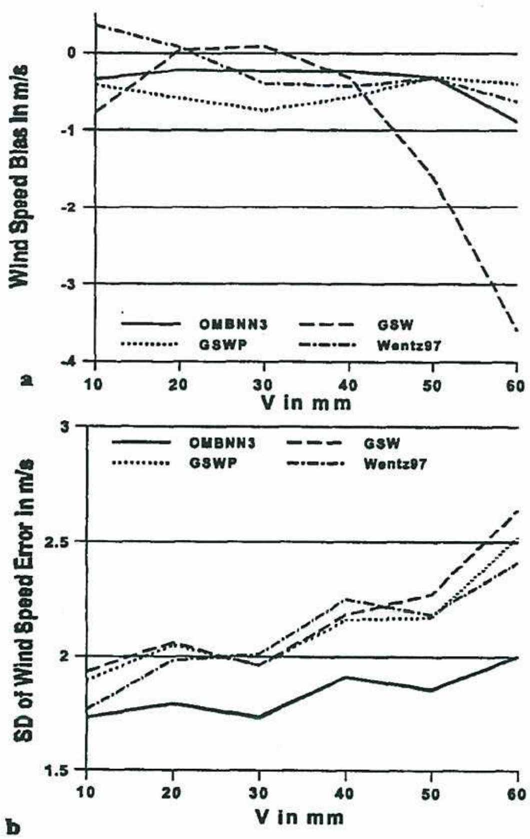
$$G_q = b_q + a_q tanh\{\sum_{j=1}^{k} \omega_{qj} [tanh(\sum_{i=1}^{n} \Omega_{ji} T_i + B_j)] + \beta_q\}, \quad q = 1,\ldots,m \tag{4}$$

where the matrix $\mathbf{\Omega}_{ji}$ and the vector $\mathbf{B}_j$ represent weights and biases in the neurons of the hidden layer; $\boldsymbol{\omega}_{qj} \in \Re^{k \times m}$ and the $\boldsymbol{\beta}_q \in \Re^m$ represent weights and biases in the neurons of the output layer; and a_q and b_q are scaling parameters.

For wind speed, high quality ground truth observations, including buoy and ocean weather station wind speed measurements, are available to create matchups with the SSM/I BTs. Evaluating the different algorithms was performed by comparing them with independent ground truth observations. Table 1 shows the summary wind speed statistics for clear and clear + cloudy conditions.

Table 1. Biases and RMS errors (m/s) for different SSM/I wind speed algorithms, for clear and clear+cloudy (in parentheses) conditions.

Algorithm	Bias	RMS Errors
Linear Regression [4]	-0.2(-0.5)	1.8 (2.1)
Nonlinear Regression [5]	-0.1(-0.3)	1.7 (1.9)
Physically-Based [6]	0.1(-0.1)	1.7 (2.1)
OMBNN3 [3]	-0.1(-0.2)	1.5 (1.7)



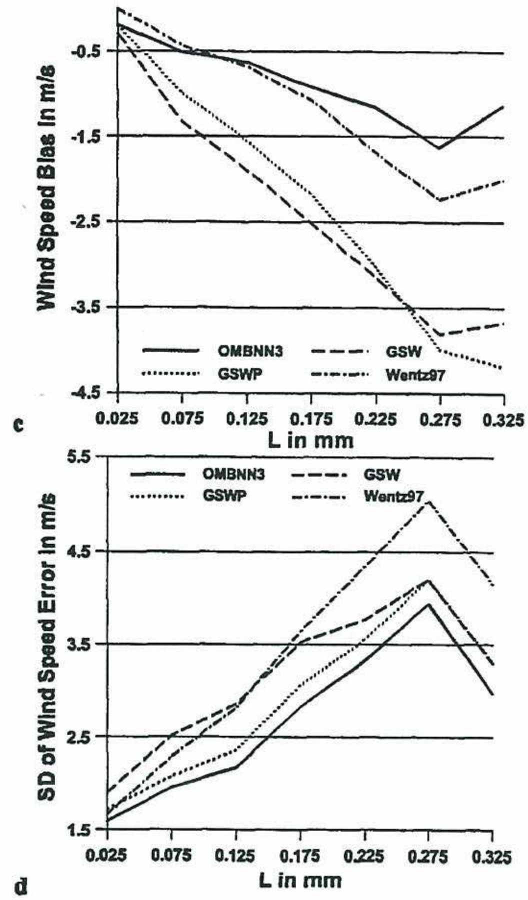


Fig. 2. Systematic (wind speed bias - *a* and *c*) and random (standard deviation (SD) of wind speed error - *b* and *d*) errors in wind speed retrieved by four different algorithms as functions of columnar water vapor, *V*, (*a* and *b*) and columnar liquid water, *L*, (*c* and *d*). Solid line - OMBNN3, dotted line - GSWP, dashed line - GSW, and dash-dotted line the PB algorithm.

This table compares four algorithms: two single-parameter algorithms GSW [4], GSWP [5], and two multi-parameter algorithms PB [6], and OMBNN3 [3] using the available matchups (> 15,000) for three SSM/I instruments F8, F10, and F11. As mentioned earlier, one of the advantages of the OMBNN3 algorithm is its ability to retrieve not only wind speed but also three other parameters: columnar water vapor *V*, columnar liquid water *L*, and *SST* simultaneously. Here we show how simultaneous retrievals of the entire vector of related geophysical parameters (2) improves the accuracy of the wind speed retrievals by taking into account the co-variability of these parameters. Fig. 2 shows the systematic and random errors (bias and SD) in wind speed retrieval as functions of V and L for the GSW, GSWP, PB, and OMBNN3 algorithms. These statistics were calculated using more than 12,000 matchups. Including the nonlinear water vapor correction in GSWP reduces the bias and its dependence on water vapor concentration; however, it does not reduce the dependence on liquid water concentration. The OMBNN3 and PB algorithms, which both employ the simultaneous multi-parameter retrieval approach, reduce the bias, and the dependence of the bias, on both water vapor and cloud liquid water concentrations. The random errors for the OMBNN3 algorithm are significantly smaller and demonstrate weaker dependencies on the related atmospheric parameters than do the errors for the other algorithms.

We have selected two algorithms, GSWP (currently used operationally by Fleet Numerical Meteorological and Oceanographic Center) and OMBNN3 (currently used operationally at National Centers for Environmental Prediction) which demonstrate the best overall performance in accordance with Table 1 and Fig. 2. Next, we perform a more detailed comparison and error analysis for these two algorithms. At least two different sets of retrieval flags have been developed for SSM/I wind speed retrievals (RF and SF). These retrieval flags serve as delimiters for BT over the ranges of applicability for a given algorithm. They also are used to indicate reliability and accuracy of retrieved wind speed. BT retrieval flags are closely related to the amount of cloud liquid water in the atmosphere. Fig. 3 demonstrates this close correlation.

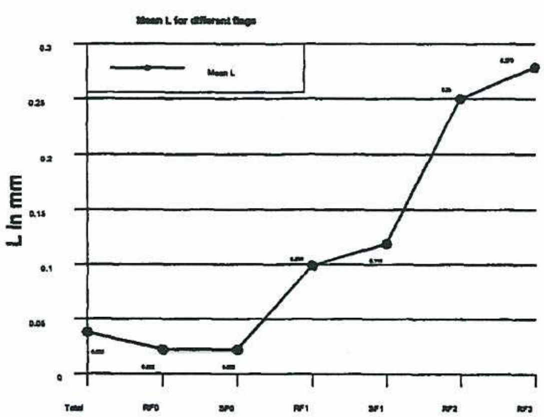


Fig. 3. Mean values of columnar liquid water, L, corresponding to different retrieval flags.

Fig 4 shows a comparison of two selected algorithms for different retrieval flags. Panel (a) shows the number of matchups for different flags. Panel (b) shows wind speed

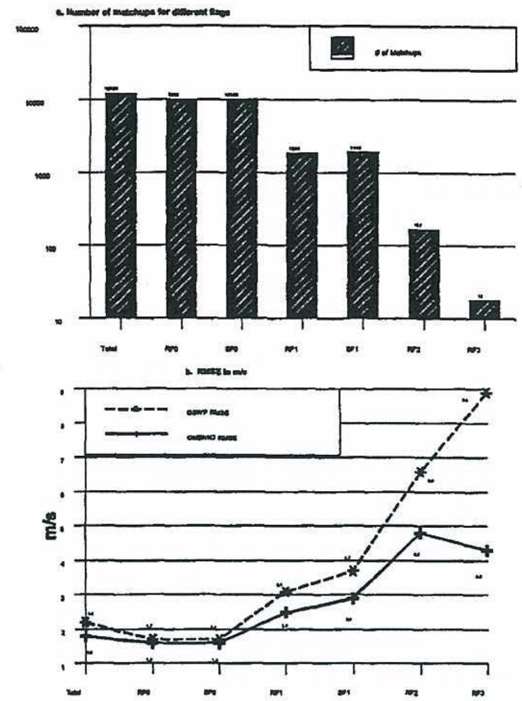


Fig. 4. (a) Number of matchups corresponding to different retrieval flags. Wind speed RMSE (b) for different retrieval flags, and for two different retrieval algorithms, GSWP (dashed line) and OMBNN3 (solid line).

RMSE for different flags. Flags RF0 and SF0 are similar (SF0 includes a small portion of RF1 in addition to RF0) both in terms of the number of matchups included, and the corresponding statistics. The SF1 flag includes the rest of RF1 and RF2 and RF3.

Figs. 3 and 4 show that OMBNN3, which outperforms GSWP under all conditions, demonstrates much better performance than GSWP especially at SF1, RF2, and RF3 when the amount of cloud liquid water increases significantly. Thus, we conclude that the SF flags are well suited for use with the NN algorithms. Of considerable significance operationally is the fact that the OMBNN3 algorithm has extended the retrieval domain from clear (SF0 or RF0), to clear plus cloudy (SF0 + SF1) conditions, yielding an increase in areal coverage of ~15% globally. This result is particularly important for obtaining more complete coverage of synoptic weather systems such as extratropical cyclones which are typically characterized by higher levels of moisture and wind speed.

Conclusions

A new generic approach for developing multi-parameter empirical retrieval algorithms based on the NN technique is introduced. It is shown that multi-parameter TF is essentially a continuous mapping. NNs are well suited for continuous mapping, with improvements over standard approaches like linear and nonlinear regressions. Multi-parameter retrievals preserve the correct physical relationships between the retrieved parameters by partitioning the variance among the variables in an appropriate manner. This approach may find use in many other remote sensing applications as well.

Presented approach has been applied to develop a new empirical, multi-parameter SSM/I retrieval algorithm OMBNN3 which is compared with other global SSM/I retrieval algorithms. This algorithm simultaneously retrieves wind speed, columnar water vapor, columnar liquid water, and SST using only SSM/I brightness temperatures. The accuracy of the wind speed retrievals from the new OMBNN3 algorithm (algorithm RMS error 1.0 m/s under clear, and 1.3 m/s under clear plus cloudy conditions) is systematically higher than the accuracy of wind speed retrievals for the other algorithms tested, for all SSM/I instruments. This improvement is valid under all weather conditions and for all wind speeds where retrievals are possible. The OMBNN3 algorithm has extended the areal coverage by ~15% globally and even higher in areas of increased meteorological activity (storms and fronts) which have higher levels of moisture and wind speed.

The new algorithm successfully separates the wind speed, columnar water vapor, columnar liquid water, and SST signals contained in the SSM/I brightness temperatures. The simultaneous retrieval of related atmospheric and surface parameters is also beneficial when cloudy and very cloudy weather conditions are present. Because the brightness temperature retrieval flags which we use are essentially statistical (based on global statistics), they are not highly sensitive to local conditions. In some cases this may lead to degraded retrievals; therefore, any additional information about related local atmospheric and surface conditions which can be derived from the same brightness temperatures may improve these brightness temperature retrieval flags. Local atmospheric and surface parameters (*V, L,* and *SST*), which the OMBNN3 algorithm now produces simultaneously with wind speed, help to describe the instantaneous state of the atmosphere more completely, and, therefore may help to improve the retrieval flags and to further improve the accuracy of retrievals under cloudy conditions.

References

[1] Krasnopolsky V.M., W.H. Gemmill, and L.C. Breaker, "A multi-parameter empirical ocean algorithm for SSM/I retrievals," *Canadian J. Rem. Sens.*, in press, 1999

[2] Funahashi, K., "On the approximate realization of continuous mappings by neural networks," *Neural Networks*, v. 2, pp.183-192, 1989
Chen, T., and Chen, H., "Approximation capability to functions of several variables, nonlinear functionals and operators by radial basis function neural networks," *Neural Networks*, v. 6, 904-910, 1995
---- "Universal Approximation to nonlinear operators by neural networks with arbitrary activation function and its application to dynamical systems", *Neural Networks*, v. 6, 911-917, 1995

[3] Krasnopolsky, V.M., W.H. Gemmill, and L.C. Breaker, "A new transfer function for SSM/I based on an expanded neural network architecture," Technical Note, OMB contribution No. 137, NCEP/NOAA, 1996

[4] Goodberlet,M.A., C.T.Swift and J.C.Wilkerson, "Remote sensing of ocean surface winds with the special sensor microwave imager," *JGR*, v. **94**, 14574 - 14555,
1989

[5] Petty, G.W., "A comparison of SSM/I algorithms for the estimation of surface wind", *Proceedings Shared Processing Network DMSP SSM/I Algorithm Symposium*, 8-10 June, 1993

[6] Wentz F.J., "A well-calibrated ocean algorithm for special sensor microwave/imager", *JGR*, v. **102**, 8703-8718, 1997