OCEAN SURFACE RETRIEVALS FROM THE SSM/I USING NEURAL NETWORKS[1]

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ABSTRACT

A new neural network SSM/I transfer function (OMBNN3) which retrieves wind speed, columnar water vapor (*V*), columnar liquid water (*L*), and *SST*, using only satellite data (five SSM/I brightness temperatures) is introduced and compared with the current operational algorithm for retrieving surface wind speed and NN algorithms developed earlier. The new NN algorithm systematically outperforms all algorithms considered for all SSM/I instruments (F8, F10, F11 and F13), under all weather conditions where retrievals are possible, and for all wind speeds. It also retrieves *V* and *L* with an accuracy close to that of cal/val (for *V*) and Weng and Grody (for *L*) algorithms, and produces low resolution SSTs with moderate accuracy. OMBNN3 demonstrates significantly better performance at higher wind speeds (and higher latitudes) than previous NN-based algorithms, generating wind speeds up to ~23 m/s for the available test data, and has a theoretical upper limit of about 32 m/s.

1.0 INTRODUCTION

A new neural network (NN) SSM/I transfer function (OMBNN3) is presented which retrieves wind speed (*W*), columnar water vapor (*V*), columnar liquid water (*L*), and *SST*, using only satellite data (five SSM/I brightness temperatures (BTs)). Also presented is a detailed comparison of the new algorithm with the current operational (GSW) algorithm (Goodberlet, et al., 1989) and several NN algorithms developed earlier (Krasnopolsky et al., 1995a, 1995b).

SSM/I wind retrieval algorithms encounter two basic problems: (1) atmospheric moisture and (2) high wind speeds. It was shown (Stogryn et al., 1994; Krasnopolsky et al., 1995a), that an adaptive nonlinear approach such as NNs can accommodate the nonlinearity of the SSM/I transfer function caused by atmospheric moisture, extending the retrieval capability under cloudy atmospheric conditions. However, it is not yet clear to what extent retrievals can be extended under cloudy conditions. Although an upper limit for retrievals (~0.5 mm in terms of columnar liquid water) has been suggested, it is clear that in particular situations this limit may be significantly lower (e.g., in rain). Because high moisture events are relatively rare, they are poorly represented in development data sets which makes this problem even more difficult. The new OMBNN3 algorithm which estimates two moisture criteria, *V* and *L* together with the wind speed, provides an additional information about the level of moisture and control on the accuracy of wind speed retrievals.

Several problems arise at high wind speed (see Krasnopolsky et al., 1996a): (1) saturation of BT at high wind speeds due to saturation of the area of the ocean surface covered by the persistent fraction of whitecap foam, (2) increasing noise in BT from the transient part of whitecap foam fraction at high wind

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speeds, and (3) very few buoy observations exist at higher wind speeds ($W > 15$ m/s). The linear GSW retrieval algorithm can, in principle, generate high wind speeds; however, validation of this algorithm using buoy observations shows that it has high scatter at high wind speeds and generates high wind speeds in some cases even when observed wind speeds are low. The first NN algorithms, SBB NN (Stogryn et al., 1994) and OMBNN1 (originally called SER NN in Krasnopolsky et al., 1995a), demonstrated retrieval accuracy which was significantly better than that for GSW, however, they were not able to generate wind speeds higher than 16-18 m/s. An improved high wind speed NN algorithm was developed, OMBNN2 (Krasnopolsky et al., 1995b), which is capable of generating higher wind speeds (up to 20-21 m/s without a bias correction). It uses a bias correction to extend retrievals up to wind speeds of to 25 -26 m/s. However, this bias correction is instrument and/or satellite dependent. Here we introduce a new NN algorithm[3] which generates wind speeds up to 23-24 m/s based on the available data sets without any bias correction (theoretical high wind speed limit for OMBNN3 is about 32 m/s) and whose accuracy does not depend significantly on the instrument and/or satellite.

The development of the new OMBNN3 algorithm was possible due to (1) new matchup data, and (2) a new approach for empirical retrievals using NNs. In Section 2, the architecture of the new OMBNN3 algorithm, the data used and the NN training process are described. In Section 3 we perform a detailed validation of the OMBNN3 algorithm, using different criteria and matchups for all SSM/I instruments.

2.0 THE NEW ALGORITHM

The first-generation wind speed retrieval algorithms, including the GSW algorithm , SBB algorithm, OMBNN1, and OMBNN2 followed a standard empirical approach. They retrieved only one value (e.g., wind speed), regressing it on the satellite measurements (e.g., BTs), as

$$W = f\,(BT) \qquad (1)$$

where BT is the brightness temperature vector and f is a regression function (NN in our particular case). Representation (1) assumes (usually by default) that the data set which is used is complete (representative) enough to eliminate dependencies of W on other physical parameters (liquid water, water vapor, SST, etc.) through averaging. This assumption and, hence, representation (1), is obviously not correct at $W > 10 - 15$ m/s where the buoy/SSMI matchup data are sparse, and dependencies of the wind speed on V, L, and SST are not removed through averaging. These dependencies create additional noise with respect to wind speed at higher wind speeds. In this case, (1) gives a biased estimate for the wind speed with a large scatter (large bias and standard deviation).

NNs allow us to solve this problem without including V, L and SST as additional arguments in (1), which is the standard solution, that is not suitable for an operational algorithm. The new NN algorithm (OMBNN3) can be symbolically written as,

$$Y = g\ (BT) \qquad (2)$$

where the output vector is $Y = \{W, V, L, SST\}$, the input vector is $BT = \{T19V, T19H, T22V, T37V, T37H\}$ and g is a NN. The NN, g, which implements (2) has 5 inputs and 4 outputs, it also has one hidden layer with 12 nodes. Including additional outputs in the NN architecture improves the training process, decreases the number of local minima in the error function, and stabilizes and accelerates convergence in the training process. The NN was trained, using the weighting scheme for high wind speed data described in

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[3]The corresponding FORTRAN code which implements OMBNN3 is available upon request from Vladimir Krasnopolsky, e-mail address: wd21kv@sgi78.wwb.noaa.gov, tel. 301-763-8133.