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ATMOSPHERIC INSTABILITY PARAMETERS DERIVED FROM MSG SEVIRI OBSERVATIONS

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1. INTRODUCTION

Convective systems can develop in a thermo-dynamically unstable atmosphere. Such systems may quickly reach high altitudes and can cause severe storms. Meteorologists are thus especially interested to identify such storm potentials when the respective system is still in a preconvective state. A number of instability indices have been defined to describe such situations. Traditionally, these indices are taken from temperature and humidity soundings by radiosondes. As radiosondes are only of very limited temporal and spatial resolution there is a demand for satellite-derived indices. The Meteorological Product Extraction Facility (MPEF) for the new European Meteosat Second Generation (MSG) satellite envisages the operational derivation of a number of instability indices from the brightness temperatures measured by certain SEVIRI channels (Spinning Enhanced Visible and Infrared Imager, the radiometer onboard MSG). The traditional physical approach to this kind of retrieval problem is to infer the atmospheric profile via a constrained inversion and compute the indices then directly from the obtained profile. As this algorithm would impose a too high computer load on the MPEF system, the operational MPEF will use a statistical approach: The measured brightness temperatures together with further predictors are used to derive each instability index, where the statistical relations between these parameters are gained from a neural network and appropriate training data. Both methods are currently installed in the Eumetsat MPEF prototype environment and are tested on GOES sounder data. This paper shortly describes the two methods and shows a detailed comparison between the two methods and to independent radiosonde data. It should be noted that both methods only allow the derivation of instability indices over cloudfree areas.

2. DEFINITION OF INSTABILITY INDICES

Various studies have been performed to relate certain instability measures taken from radio soundings to the occurrence of severe weather. It became soon clear that there is no unique index for all synoptic situations and for all locations. This paper focuses on 4 different parameters, three classical instability indices:

K-Index:
$(T^{obs(850)} - T^{obs(500)}) + TD^{obs(850)} - (T^{obs(700)} - TD^{obs(700)})$

Lifted Index:
$T^{obs} - T^{lifted\ from\ surface}$ at 500 hPa

Maximum buoyancy:
$\Theta_e^{obs(max\ betw.\ surface\ and\ 850)} - \Theta_e^{obs(min\ betw.\ 700\ and\ 300)}$

(T is temperature, TD is dewpoint temperature, and Θ_e is equivalent potential temperature, numbers 850, 700, 300 indicate respective hPa level in the atmosphere)

and the precipitable water content as additionally derived parameter.

3. DESCRIPTION OF ALGORITHMS

3.1 The Physical Retrieval

An iterative solution to the inversion equation (e.g. Ma et al. (1999)) tries to infer the temperature and humidity profile from the measured brightness temperatures, the back-ground atmospheric profile (usually referred to as first guess) and the associated error/noise matrices. In each iteration step, the inversion needs knowledge about the change of brightness temperature with the change of the atmosphere in each level, which is described by the Jacobians of a radiation model. It is the computation of these Jacobians together with the inversion of large matrices which make this method very CPU intensive. This method was chosen for the current operational retrieval of lifted index and precipitable water a for the GOES sounder at CIMSS (Menzel et al., 1998), and the Eumetsat prototype only differs from the CIMSS approach by using RTTOV as the radiation model (Saunders et al., 1999). RTTOV has the advantage of a much faster computation of the Jacobians. In application to the GOES sounder, the algorithm uses the sounder channels 5, 7, 8, 10, 11, and 12, which are at about 13.4 µm, 12.0 µm, 10.8 µm, 7.3 µm, 6.5 µm, and 6.2 µm wavelength, resp.. In a possible future application to SEVIRI, the method will also use 6 channels, and as SEVIRI will not have a 6.5 µm channel, the 8.7 µm channel will be used instead. This channel selection ensures that sufficient information concerning the atmospheric state is passed to the retrieval algorithm, e.g. surface skin temperature and low level moisture via the two window channels, higher level humidity via the water vapour channels, and the higher level temperature information via the 13.4 µm channel.

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Over clouds, the algorithm cannot find a solution, i.e. the iteration scheme does not converge in these cases. Over clear skies, convergence is usually achieved after one or two iterations, and each instability index can then easily be derived from the atmospheric profile.

Tests show that the physical retrieval substantially improves the first guess data concerning the resulting instability indices, where the improvements are clearly related to the better detection of the unstable cases.

Closer inspection of the retrieved actual profiles demonstrates that the retrieval scheme mostly changes the surface skin temperature and the low level humidity profile, while it leaves the temperature profile very near to the first guess values.

For the MSG MPEF prototyping, the results of the physical method are used as a kind of reference to assess the results of the statistical approach.

3.2 The Statistical Method

This method is based on a neural network approach: The neural net is used to identify linear and non-linear relationships between a number of input values – the predictors – and one output value – the respective instability index. In general, a neural network is a computer model of individual elements commonly referred to as neurons. The input parameters to the model make up the input neurons, the output value is then the output neuron. There can be intermediate layers which are called hidden layers of any number of neurons. The neurons of the individual layers are connected by links, where each link is given a certain weight. The inputs are processed by a weighted summation and the transfer function passes the result to the neurons of the next layer, until the output is produced. During a training phase of the neural net, the weights are optimised to fit the wanted output. A neural network must thus be trained with input / output pairs, i.e. with some independent data.

In our case, we use a simple three-layer backpropagation neural network (e.g. Chauvin and Rumelhart, 1995) with 15 input neurons and one hidden layer with 20 neurons. The transfer function is the hyperbolic tangent $f(x) = \tanh(x)$.

A backpropagation network is trained by learning with clearly defined pairs of inputs and outputs. With these ‘wanted’ outputs, the neural net successively adjusts its weights in every learning cycle to minimise the error between the ‘wanted’ output and the output produced with the weights and the transfer function from the given inputs. This training cycle is repeated for a large number of input / output patterns until a minimum error is achieved. The criterion of a minimum error is also used to determine the characteristics of the input values and the number of the hidden neurons. Obvious input values are of course the six brightness temperatures in the six channels (see section 3.1) and the satellite viewing angle. Eight further parameters, which give some seasonal and diurnal time information and knowledge about the geographical location, slightly improved the performance of the net.

The real problem concerned with the neural net is to have a good training dataset: This dataset must contain a wide range of possible observations of the predictors and the output value. Otherwise the net will perform badly if it is faced with real data which were not properly reflected in the training dataset. This problem is quite evident if radiosonde data are used for training: Although the input values can be obtained from the sounding rather easily – the brightness temperatures can be calculated with a forward model – and the instability index is directly inferred from the sounding, the radiosondes still give a very poor training dataset. Due to the only twice daily (00 and 12 UTC) soundings, the diurnal cycle is not resolved, and also spatial coverage is very poor. Locations are only a fixed set of certain values, and the ocean areas are practically not covered at all. It was thus decided to use the results of the physical retrieval (taken from historical data) as training data for the neural net. This provides data for every possible location within the satellite’s field of view with good diurnal coverage. Initial results with training based on several months of GOES data showed very good agreement between the two methods.

For this training phase, data were collected of satellite measured brightness temperatures, of the pixel locations and scan times and of the respective instability index as provided by the physical method. This large dataset (about 70,000 entries of heavily sampled GOES sounder data over several months) was randomly split into three categories: One third of the data was used for the neural network training, one third was used as the so-called generalisation data within the network training, and the third section was used as an independent dataset to test the network’s performance for data unknown to the net during its learning phase. Figure 1 shows an example of this initial network test for the precipitable water content. For the other indices, there is slightly more scatter with correlation coefficients between 0.85 and 0.90.

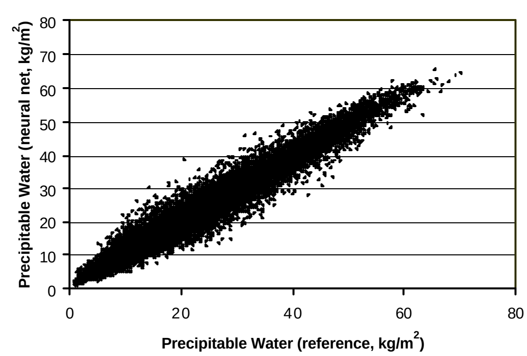
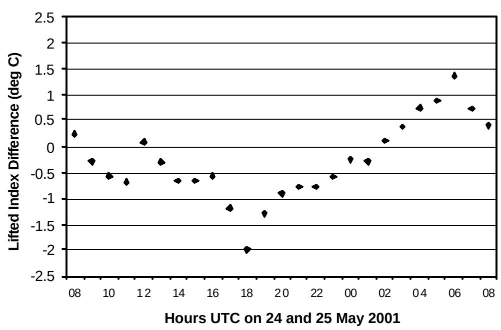


Figure 1: Scatter plot of neural network derived precipitable water compared to independent reference data from the physical method (correlation coefficient 0.97)

4. RESULTS

The two methods were applied to several GOES-8 sounder images during the months of May and June 2001. In general, good agreement was achieved between the statistical results and the results of the physical method, especially regarding the temporal evolution of unstable regions. 25 hourly images collected between 0800 UTC on 24 May 2001 and 0800 UTC 25 May 2001 comprise a sample case. During this day, a large region of highly unstable air developed over southern Texas along the coast, and an extended convective system developed in the same region in the morning hours of the 25th. Colour plots of the spatial distribution of various instability indices derived by the two methods and corresponding time loops are shown in http://www.eumetsat.de/GII.

To demonstrate the rather good performance of the statistical method with respect to the physical retrieval, Figure 2 shows the lifted index difference between the two methods as a mean over the entire GOES-8 field of view and as a mean over the region of instability.



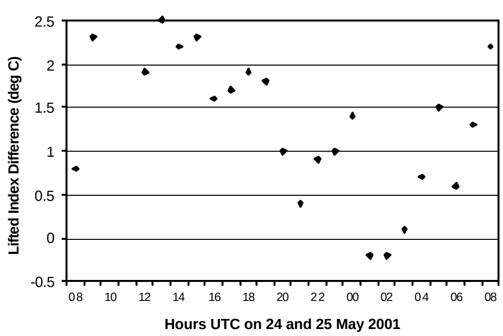


Figure 2: Difference of the lifted index between the physical and the statistical approach for the entire GOES-8 sounder fov (top) and over the region of instability over Texas and the adjacent Gulf (bottom)

Potentially unstable air is described by a negative lifted index. The positive lifted index difference shown in the bottom section of Figure 2 thus means that the statistical method indicates a slightly higher degree of instability than the physical method. This is a general behaviour of the statistical approach that is found in many examples. As the instability measure, however, is meant to be a warning against severe weather, this slight exaggeration is probably a good feature.

Comparisons with the 00 UTC radiosondes on the 25th show good overall agreement to the results of both methods. These comparisons can also be seen in http://www.eumetsat.de/GII.

In the future application to MSG, the intention is to disseminate the instability results as area averages over n*n image pixels, where n will be typically of the order of 10. There are several possibilities of how to average:

(a) a simple arithmetic mean over the pixels
(b) provide the value of the most unstable pixel
(c) average only over the unstable pixels, take the simple average over all pixels if there are no unstable ones
(d) average over the unstable pixels if their number exceeds a certain threshold, else average over all pixels

For the precipitable water content, clearly option (a) would be applicable, while for the actual instability indices option (d) would be more preferrable. Again, http://www.eumetsat.de/GII shows examples of the different averaging methods.

5. CONCLUSIONS

It can be shown that a statistical approach to the general retrieval problem of instability indices is possible and gives good results if the regression coefficients are obtained from a representative dataset. In the application within the MSG/MPEF, this method will be used as it is computationally fast and thus easily applicable on a pixel basis to each of the MSG images, which will be recorded at 15-minute intervals. The operational results of the MPEF scenes analysis will provide the cloud information so that clouds can be screened from the processing.

As a good training dataset can probably only be collected from selected runs of the physical method on actual MSG image data, the quality of the MPEF instability product is expected to increase with time as more training data becomes available which will lead to a successive improvement of the regression data.

6. REFERENCES

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