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A SYSTEM FOR MONITORING NO_2 EMISSIONS FROM BIOMASS BURNING BY USING GOME AND ATSR-2 DATA

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Abstract. In this paper, we propose a system for monitoring abnormal NO_2 emissions in troposphere by using remote-sensing sensors. In particular, the system aims at estimating the amount of NO_2 resulting from biomass burning by exploiting the synergies between the GOME and the ATSR-2 sensors mounted on board of the ERS-2 satellite. Two different approaches to the estimation of NO_2 are proposed: the former, which is the simplest one, assumes a linear relationship between the GOME and ATSR-2 measurements and the NO_2 concentration. The latter exploits a nonlinear and nonparametric method based on a radial basis function (RBF) neural network. The architecture of such a network is defined in order to retrieve the values of NO_2 concentration on the basis of the GOME and ATSR-2 measurements, as well as of other ancillary input parameters. Experimental results, obtained on a real data set, confirm the effectiveness of the proposed system, which represents a promising tool for operational applications.

1. Introduction

The European Remote Sensing Satellite (ERS) Programme has been provided Earth Observation measurements to the international user community over a time range of ten years. This has stimulated the development of Science, Public Utility and Commercial Applications in a variety of disciplines related to the monitoring of the Earth's environment. Nowadays, a very critical application concerns the monitoring of air pollution, since only few specific remote-sensing sensors are available to accomplish this task. For this reason, important efforts should be devoted to the development of remote-sensing sensors and processing methods capable to provide an accurate evaluation of air pollution. One of the most important issues concerns the development of automatic systems being able to monitor on a global scale the Nitrogen Dioxide (NO_2) emissions in the troposphere. In this context, the Global Ozone Monitoring Experiment (GOME) sensor mounted on board of the ERS-2 satellite turns out to be an effective and unique monitoring resource. The GOME products, generated operationally at the German Processing and Archiving Facility (D-PAF) at the German Aerospace Center (DLR) comprise calibrated earthshine radiances and the extra-terrestrial solar irradiance (Level 1 products) together with total column concentrations (stratosphere + troposphere) of ozone and nitrogen dioxide as well as cloud information (Level 2 products). To retrieve the tropospheric contribution to the column densities of trace gases in nadir viewing, additional information and processing are required. To this purpose, the GOME data have been treated in a variety of ways to obtain tropospheric information. A possible approach is to use the knowledge of the different temporal and horizontal scales of constituents in the stratosphere and troposphere. In particular, on the one hand, the tropospheric amount of NO_2 usually exhibits specific local behaviours; on the other hand, the stratospheric amount of NO_2 exhibits a general global behaviour. Also the transport in the stratosphere is appreciably greater than in the troposphere, so that a homogeneity of the NO_2 stratospheric column is to be expected (Leue, C. et al., 1999). An alternative vertical column (VC) approach for retrieving tropospheric information is to use measurements "on-cloud" and "off-cloud" to determine the amount of NO_2 below the cloud. However, the different albedos and the resulting photolysis field above the cloud introduce complications (TROPOSAT, 2000). Another method for the retrieval of tropospheric NO_2 is based on a combined assimilation retrieval approach, which takes into account the stratospheric background, the sensitivity to the vertical profile, clouds and the surface albedo.

Although several components contribute to NO_2 emissions (e.g. urban pollution), biomass burning is the most important source of Nitrogen Dioxide (Casadio et al. 1999, Zehner et al. 1999). For this reason, in this work we focus on biomass burning. In particular, a novel methodology is presented, which performs NO_2 emission estimation by exploiting the synergy between the GOME and the Along Track Scanning Radiometer (ATSR-2) instruments, both mounted on board of the ERS-2 satellite. In particular, two main approaches to NO_2 estimation are proposed: i) a simple linear approach that provides estimations of NO_2 emissions on the basis of GOME and ATSR-2 data on a regional scale; ii) a nonlinear approach that provides NO_2 estimations on a global scale by exploiting both a large set of input parameters and a radial basis function (RBF) neural network. The resulting system represents a novel attempt to retrieve NO_2 emissions due to biomass burning on a regional or global scale by exploiting the synergy between GOME and ATSR-2 sensors.

The paper is organized into six sections. The next section briefly describes the GOME and ATSR-2 sensors and the related data. Section 3 introduces the problem formulation and the simplifying assumptions considered in the development of the proposed system. Section 4 deals with the proposed linear and nonlinear approaches. The data sets used in the experiments are detailed in Section 5, together with the experiments results. Finally, conclusions are drawn in Section 6.

2. Sensor and data description

The methodology proposed exploits the synergy between GOME and ATSR-2 sensors mounted on board of the ERS-2 satellite. In the following, these sensors and the related data are briefly described.

Owing its nadir viewing geometry, GOME sensor provides the possibility to measure the total column amount of atmospheric constituents down to the Earth's surface. Its main scientific objective is to measure the global distribution of ozone and other trace gases through spectral analysis of the sunlight scattered from the Earth's atmosphere and/or reflected by the surface in the spectral region 240-790 nm. The GOME instrument is a double monochromator and the entering light is split into four separate spectral bands. In each of the four spectral bands, the light is dispersed by a diffraction grating and focused onto monolithic silicon linear detector array comprising 1024 individual detector pixels. Detailed description of the instrument design and operation can be found in (GOME Users Manual, 1995). GOME Level 2 products consist of slant and vertical amount of atmospheric constituents (ozone and nitrogen dioxide), and related uncertainties, retrieved from calibrated geolocated radiances. They also include essential information on cloud parameters. Here, we use both NO_2 vertical column data and the cloud information to select cloud free scenes (this task is accomplished by imposing a threshold equal to 0.3 on the GOME cloud fraction factor). It is difficult to evaluate precisely the accuracy of the GOME nitrogen dioxide product due to various problems, such as the diurnal variation of NO_2 and the profile shape effect on the Air Mass Factor (AMF). The overall accuracy of the GOME NO_2 total column is estimated to fall within the 5% to 20% ranges (http://earth.esa.int/gome_report99).

The conical scan of the ATSR-2 radiometer measures nadir and forward reflectances in four solar and three thermal channels with a spatial resolution of 1 km. An important application of ATSR-2 data is the detection of forest fires and other hotspots on the Earth's surface. To this end, a widely used approach is to associate pixels with an average temperature greater than 312K to hotspots. The ATSR-2 product used here is the Monthly Global Fire Maps (Level 3 product, downloadable at http://shark1.esrin.esa.it/FIRE/AF/ATSR/). The user of the Fire product must take into account both the algorithm limitations due to the presence of clouds and atmospheric effects, and the fact that the fire temperature and extension are not taken into account in the processing. The ATSR night-time data used to determine the presence of hotspots (fires) are compose of four spectral bands: 1.6, 3.7, 11.0, 12.0 μm. The detection capabilities depend on the fire temperature; they can be estimated as follows: from 0.1 ha at 600K to 0.01 ha at 800K, for a background temperature of 300K. The advantages of ATSR-2 are that, due to the night-time detection, no artefacts due to solar reflection are possible. Moreover, the absence of drift of the ERS orbit allows year-to-year comparisons, and the high radiometric sensitivity allows one the detection of little/not extended fires. Two well-known problems in the hotspot retrieval by using ATSR-2 data are: i) ATSR-2 frames overlap (some fires can be detected twice); ii) only night-time fires are detected (this involves a global underestimation of the number of hotspots). It is worth noting that an ATSR FIRE Atlas product is presently in a validation phase (Arino et al. 2001).

3. Problem formulation and simplifying assumptions

The problem of the estimation of the amount of NO_2 in the troposphere by using data acquired by the GOME and ATSR-2 sensors is very complex. The complexity depends on several factors that decrease the precision of the measurements acquired by the sensors and increase the difficulty in the sensor integration. In particular, the following factors should be considered in addition to those described in the previous section (i.e. presence of clouds, uncertainties of data):

a) GOME and ATSR-2 instruments acquire measurements at different times. In particular, GOME collects data during the day, whereas ATSR acquires data about hotspots during the night.

b) GOME measurements are related to the total column amount of atmosphere constituents down to the Earth surface. Consequently, they are influenced both from the stratospheric and the tropospheric components of NO_2. This makes it complex to isolate the NO_2 component present in the troposphere.

c) The NO_2 production in absence of fires (let us call it "normal"), which should not be considered in our estimation because uncorrelated with burning biomass, has a seasonal cycle that depends on the latitude of the geographical area investigated.

d) The NO_2 plumes generated by combustion may be transported by the wind also far from the area of production. This may affect the spatial accuracy of the GOME measurements.

e) The NO_2 produced by a forest fire depends on the amount of burned biomass, and hence on the land-cover of the area considered.

By taking into account the aforementioned issues, in the definition of the proposed system we considered the following simplifying assumptions:

1) *The plume movements can be modelled with a Gaussian distribution:* we model with a Gaussian distribution the diffusive behaviour of NO_2 in the troposphere (Sharan et al. 1996).
2) *No significant changes took place between the acquisitions of GOME and ATSR data*: this assumption, that in some cases may be critical, makes it possible to establish a correlation between the GOME and the ATSR measurements.
3) *The stratospheric amount of NO_2 is constant over time:* according with Leue et al. (1999), we make the assumption that the stratospheric amount of NO_2 does not change over time. This reasonable assumption results very useful in the formulation of the proposed approach to separate the tropospheric and stratospheric NO_2 components.

4. Proposed System

In the proposed system, the GOME and ATSR measurements are integrated in order to establish a correlation between the amount of NO_2 present in the troposphere and hotspots related to active fires on the ground. Two different approaches to the NO_2 estimation are presented: a linear approach and a nonlinear approach based on RBF neural networks. The two approaches are described in the following sub-sections.

4.1. Linear approach

The linear approach is the simplest one. The rationale of such an approach is that the amount of NO_2 produced in a given area by biomass burning has a linear dependence on the number of hotspots detected in the considered area. This involves the assumption that a single hotspot emits a fixed amount α of NO_2. Even though such an assumption may be critical, it allows one to obtain estimate of NO_2 produced in a given area by biomass burning with a level of accuracy acceptable for many applications.

The linear approach is composed of two phases: estimation of the average amount α of NO_2 emissions related to each hotspot (training phase); estimation of NO_2 emissions on the basis of both the number of hotspots detected by ATSR-2 sensor and the α value previously estimated (operative phase).

The training phase is carried out in three steps: i) detection of abnormal amounts of NO_2 in the troposphere by using GOME data; ii) integration of GOME and ATSR-2 data for estimating the relationship between fires and GOME measurements; iii) estimation of the coefficient α. These steps are described in greater details in the following.

i) On the basis of the assumption that the stratospheric amount of NO_2 can be considered almost constant in time, we propose to estimate the tropospheric abnormal NO_2 emissions by computing temporal variations of GOME measurements versus the behaviour of historical series of data.

ii) Since biomass burning produces NO_2 gases, the amount of NO_2 in a given area is related to the number of hotspots detected in the considered site. Let us denote x_j^{GOME} the position of the pixel centre related to the *j-th* GOME measure and x_i^{ATSR} the position of the *i-th* hotspot detected by the ATSR-2 sensor. In order to estimate the influence that the *i-th* hotspot has on the *j-th* GOME measure, the following weighting function $f\left(x_j^{GOME}, x_i^{ATSR}\right)$ is adopted:

$$f\left(x_j^{GOME}, x_i^{ATSR}\right) = \begin{cases} e^{-\frac{d^2}{d_{th}}} & d \le d_{th} \\ 0 & d > d_{th} \end{cases} \quad (1)$$

where d is the distance between x_j^{GOME} and x_i^{ATSR}, and d_{th} is a threshold value that is computed to take into account the diffusion of NO_2 gases. By summing the components related to all the detected hotspots, we obtain an estimation of the total influence $F\left(x_j^{GOME}\right)$ of forest fires on the j-th GOME measure:

$$F\left(x_j^{GOME}\right) = \sum_i f\left(x_j^{GOME}, x_i^{ATSR}\right) \tag{2}$$

Consequently, $F\left(x_j^{GOME}\right)$ can be considered as an equivalent number of hotspots located in x_j^{GOME} and producing an amount of NO_2 equal to the one actually measured by the GOME sensor.

iii) A linear regression between abnormal NO_2 values identified in i) and the correspondent $F\left(x_j^{GOME}\right)$ values computed in ii) is applied in order to estimate the average amount α of NO_2 emissions related to each hotspot.

It is worth noting that in the training phase of the linear approach it is mandatory to have historical series of GOME and ATSR-2 data of the investigated area.

During the operative phase, only ATSR-2 data are required. The estimation of NO_2 emissions related to the considered geographical area (let NO_2^{trop} denote such an amount) is carried out according to the following simple equation:

$$NO_2^{trop} = \alpha N \tag{3}$$

where N is the total number of hotspots detected in the considered geographical area by analysing the ATSR-2 data.

Since the analysis of different geographical areas reveals that the amount of NO_2 produced by a single hotspot depends on several factors (e.g. the latitude and the land-cover type that characterise the investigated area), the α value estimated for a specific geographical site can be used only in a neighbourhood of the considered area.

4.2 Nonlinear approach based on RBF neural networks

The proposed approach based on RBF neural networks considers the abnormal amount of NO_2 produced in troposphere (NO_2^{trop}) as a nonlinear function depending on several parameters, i.e.

$$NO_2^{trop} = g(\underline{J}) \tag{4}$$

where each component of the vector $\underline{J}$ is a physical parameter that influences the NO_2 generated. In the this approach, we consider the following input parameters for the NO_2 estimation:

- *Vegetation index*: different types of land-covers (e.g. different types of "fuel") produce different amounts of NO_2.
- *Latitude*: important indication on the amount of NO_2 produced by biomass-burning and present in the troposphere can be retrieved by the knowledge of the investigated area latitude. In fact, latitude provides hints about: i) the combustion speed (such a parameter depends on the heat); ii) the land coverage; iii) the seasonal cycle characterising the normal amount of NO_2.
- *Number of fires in the considered area*: the NO_2^{trop} increases when the number of fires increases. Therefore, the information on the number of hotspots provided by the ATSR-2 sensor plays a fundamental role in the estimation process.
- *Spatial position of fires with respect to the GOME measurements*: the sensitivity of the GOME measurements to hotspots depends on the relative position between the GOME IFOV and fires.
- *Season*: the seasonal period influences the natural cycle of the NO_2. Consequently, it should be considered in the estimation process.

The function $g(.)$, which defines the relation between the aforementioned input parameters and the estimated NO_2, is learned by the neural network in the training phase on the basis of selected examples.

The choice of adopting an RBF neural model depends on the ability of this kind of network to solve nonlinear problems of function estimation and regression (Powell 1987, Broomhead and Lowe 1988, Hatman et al. 1990, Park and Sandberg 1991) and on the advantages exhibited by this kind of neural model over other ones. In particular, one of the main advantages consists in a good trade-off between the complexity of the training phase and the obtained accuracy (Bruzzone and Fernández Prieto 1999). Generally, a Gaussian RBF neural network is composed of three layers (an input, a hidden and an output layer). Input neurons (as many as input features) just propagate input features to the next layer. Each neuron in the hidden layer is associated with a radial basis kernel function (usually a Gaussian function φ_i characterised by a centre μ_i and a width σ_i). In one-dimensional regression problems, the output layer is composed of one neuron that computes a simple weighted summation of the responses of the hidden neurons to a given pattern described by the input feature vector. The connections between the hidden neurons and the output neuron are associated with numerical values called "weights" (Figure 1 shows the architecture of the RBF neural network used in the proposed nonlinear system). In the training phase, the centre $\underline{\mu}_j$ and the width $\underline{\sigma}_j$ of each gaussian activation function of hidden units, as well as the weights between the hidden units and the output unit, are computed. This can be accomplished according to classical training procedures (Moody and Darken 1989, Park and Sandberg 1991, Bruzzone and Fernández Prieto 1999). In particular, in our approach, the simple algorithm proposed by Moody and Darken (1989) is adopted. We refer the reader to (Bianchini et al. 1995, Bruzzone and Fernández Prieto 1999) for greater details on RBF neural networks and on their training procedures.

The training on the neural network is based on the previously discussed assumption that the stratospheric amount of NO_2 can be considered almost constant in time. Accordingly, the tropospheric abnormal NO_2 emissions can be estimated by computing temporal variations of GOME measurements versus the behaviour of historical series of data. Such estimations are used in the learning of the network. In particular, the neural network learns the function $g(.)$ that relates all the input parameters to the different estimates of the tropospheric abnormal NO_2 emissions. During the operative phase, the neural architecture provides the estimation of NO_2 emissions, given the correspondent input vector.

As compared to the linear approach, the nonlinear approach exhibits some important advantages:

1. it is not based on the assumption that the relation between the tropospheric NO_2 emissions due to biomass burning and the forest fires that affect the considered geographical area is linear. Consequently, more accurate estimates of the tropospheric abnormal NO_2 amount are expected;
2. it is able estimate emissions also in areas different from the ones used in the training phase (thanks to the generalisation ability of the neural network). As a consequence, the nonlinear approach can be also applied to geographical areas where time series of GOME and ATSR-2 data for the estimation of α are not available.

Concerning the last point, as described in Section 4.1, the linear approach requires the computation of an α value that depends on the specific geographical area considered. The function $g(.)$ (i.e., the relation between the set of all the parameters $\underline{J}$ and the amount of NO_2 estimated by the nonlinear approach) implicitly deals with this dependence, thus allowing one to analyse geographical areas for which the α value is not explicitly known. Consequently, an important difference between the two approaches is the scale at which they are operative. On the one hand, the linear approach allows one to estimate the amount of NO_2 at a local scale, on the other hand, the nonlinear approach is suitable for developing a global scale monitoring system.

5. Experimental results

In order to assess the effectiveness of the proposed method, a data set related to different geographical areas was considered. In particular, five areas (i.e. Africa Coast, Australia, Congo, Mexico and North Brazil) characterised by different land-cover types and latitudes were selected. Multitemporal sequences of GOME and ATSR-2 data acquired on the selected areas between November 1996 and May 1999 were considered.

To evaluate the effectiveness of both the linear and the non-linear approaches, multitemporal data were divided into two different series. Data acquired between November 1996 and June 1998 were used for the training phase; data acquired between July 1998 and May 1999 were used for the test of the proposed methods. A detailed description of the training and test sets is given in Table 1. In addition, in Table 2, the minimum and maximum NO_2 concentration values derived from the GOME measurements for each one of the considered areas are reported.

5.1 Results obtained with the linear approach

The linear approach was applied separately to each area. First of all, anomalous amounts of NO_2 in the troposphere were detected on the basis of the analysis of training samples. In particular, samples of the training data not affected by biomass burning (i.e. pixel with $F\left(x_j^{GOME}\right)=0$) were identified. Then the average (computed both in the time and in the spatial domains) of the NO_2 values measured by the GOME sensor on these samples was derived. Under the assumptions considered in Section 3, the resulting average points out the normal amount of NO_2 present in the atmosphere over the considered area. Abnormal amounts in the troposphere were thus obtained by differencing the GOME measurements and the aforementioned normal amount of NO_2. As an example, Figure 2 shows the abnormal amounts of NO_2 computed for a specific pixel of the Africa Coast area in the period between November 1996 and June 1998 (see the green profile). In the same figure, red marks point out the values assumed by the function $F\left(x_j^{GOME}\right)$. At this point, the value of the α coefficient was retrieved according to the methodology described in section 4.1. Finally, the amount of NO_2 produced in the considered area is estimated according to equation (3). Figure 3 shows the profile of such an amount computed for the Africa Coast area in the period between July 1st, 1998 and May 31st, 1999.

In order to obtain a quantitative evaluation of the effectiveness of the proposed approach, the amounts of NO_2 due to biomass burning were compared with the reference values (i.e. the abnormal amounts of NO_2 estimated by computing the temporal variations of GOME measurements versus the behaviour of the series of test data). The resulting errors for all the considered geographical areas are reported in Table 3. As one can see, the percentage error is globally quite satisfactory. In fact, even if the Congo and the Mexico areas are characterised by errors equal to 43.6% and 35.7%, respectively, all the other errors are rather small. It is worth noting that this evaluation of results is done by taking into account that the linear method considers just ATSR-2 data in the test phase. Consequently, it is not reasonable to expect that this method provides very high accuracies; on the contrary, it should be used for deriving general indications about the NO_2 emissions behaviour in the different test sites. In order to understand in greater detail the behaviour of the approach on the Congo and Mexico areas, a deeper analysis of the GOME time series was carried out. Concerning the Congo area, the analysis revealed that the behaviour of the NO_2 emissions was very unstable during the considered historical period. Consequently, the length of the series of data used was not sufficient to compute with a good approximation the normal value of NO_2 present in the atmosphere. In this case, to increase the estimation accuracy, a longer historical series of GOME measurements would be necessary. With regard to the Mexico site, it includes the Mexico City area, which is affected by a high urban pollution. Consequently, as confirmed by additional experiments not reported in this paper, the error incurred in this site mainly depends on the urban pollution present in the aforementioned city.

Table 3 also reports the values of the α coefficient obtained for the different areas. As one can see, these values strongly depend on the geographical area considered. Consequently, the α value estimated for a specific geographical site can be used only in a neighbourhood of the considered zone; hence, the linear approach can be applied only at a regional scale. In order to support this conclusion, a further experiment was carried out. In particular, the linear approach was jointly trained on the five considered areas and then tested on all the geographical sites. The error obtained is reported in Table 4, where the estimated global value of the α coefficient is also given for comparisons with the values presented in Table 3. As one can see, the error yielded is sharply higher than the overall error achieved by analysing separately the five areas (i.e., 41.9% vs 25.5%). This confirms the linear approach as a local-scale monitoring tool.

5.2 Results obtained with the nonlinear approach

In order to assess the effectiveness of the nonlinear approach, two main experiments were carried out. The first experiment was aimed at comparing the accuracies provided by the nonlinear approach with the ones exhibited by the linear method. The second experiment was devoted at investigating the effectiveness of the nonlinear approach for developing a global-scale monitoring system. In particular, the capability of the nonlinear approach to estimate emissions in a geographical area different from the ones used in the training phase was assessed.

As the objective of the nonlinear approach is to derive a global-scale monitoring system, such an approach was jointly applied to all the selected areas. In this way, the RBF neural network can learn the complex relation existing between the set of all the input parameters $\underline{J}$ and the amount of NO_2 emissions due to biomass burning.

Let us consider the first experiment. The training phase was carried out as follows. For each one of the five selected geographical areas, the abnormal amounts of NO_2 were estimated by computing temporal variations of GOME measurements on the training data according to the method described in the previous subsection. Such variations were computed separately on each considered area. The obtained estimates were used for the training of the network. Different RBF neural network architectures (i.e. architectures with different numbers of hidden neurons) were considered. At this point, the effectiveness of the nonlinear approach was evaluated by considering the test samples. The estimated amounts of NO_2 were compared with the reference values (i.e. amounts of NO_2 computed by considering the temporal variations of GOME measurements versus the normal amount of NO_2

estimated on the test data). The percentage errors obtained are given in Table 5. A comparison between Table 3 and Table 5 points out that generally the nonlinear approach allows one to significantly reduce the errors in the estimated NO_2 with respect to the linear method. In greater detail, the nonlinear approach increases the accuracy in all the areas but the North Brazil one (for which in any case the error is acceptable). The decrease of performances on the North Brazil area mainly depends on the fact that the neural network realizes a trade-off between errors incurred on each single area and generalisation capabilities.

In the second experiment (i.e., analysis of the capability of the nonlinear approach to estimate NO_2 in areas different from the ones considered in the training set), five trials were carried out by using a leaving-one-out method. In particular, in each trial, the learning of the RBF neural network was carried out by considering four of the five available geographical areas, while the test was accomplished on the remaining site. The obtained results are shown in Table 6. As one can see, the ability of neural network to generalise allows the nonlinear approach to estimate with a high accuracy NO_2 emissions also on geographical areas different for the ones used for the training. In particular, we can observe that the decrease of accuracies between Table 5 and Table 6 are not significant.

6. Discussion and conclusions

In this paper, a novel system for estimating NO_2 emissions resulting from biomass burning has been proposed. The system performs the estimation process by integrating data acquired by the GOME and the ATSR-2 sensors mounted on board of the ERS-2 satellite.

Two different approaches have been presented for estimating NO_2: an approach based on a linear model and a nonlinear approach based on RBF neural networks.

The linear approach is based on the assumption that an equivalent amount of NO_2 emissions for each generic fire can be estimated. This estimation is carried out according to a linear regression between GOME and ATSR-2 measurements applied to historical series of remotely sensed data. In the estimation process, a specific model for deleting the stratospheric NO_2 component by the GOME measurements has been considered. On the one hand, this approach exhibits two main advantages: i) it is very simple; ii) in the operative phase the NO_2 estimation is carried out on the basis of ATSR-2 data (GOME data are only used in the training of the system for computing the equivalent amount of NO_2 associated with each fire). On the other hand, the main disadvantages of this estimation procedure consist of: i) it does not take into account the differences in the production of NO_2 often associated with different hotspots; ii) it is not able to take into account the complex relationship between the amount of NO_2 emissions present in the troposphere and the large number of parameters that influence this value; iii) it requires historical series of training data for all the geographical areas studied.

The nonlinear approach based on RBF neural networks overcomes the aforementioned disadvantages. It takes into account a set of parameters that may influence the presence of NO_2 emissions in the troposphere resulting from fires. In particular, this nonparametric approach models the complex nonlinear function that maps the input parameters in the output NO_2 estimation. The neural approach exhibits two additional important advantages: i) it does not require to define a specific linear model for each geographical area considered in the test phase; ii) thanks to the generalisation ability of the neural networks, it makes it possible to estimate NO_2 emissions also in areas for which historical series of data are not available.

Experimental results obtained on a data set related to five different geographical areas point out that the proposed approaches seem to be a promising tool for monitoring NO_2 emissions. As future developments of this work, we are considering two main issues: i) to further extend the experiments with the neural approach by considering other input parameters, so increasing the precision of the function used by the neural networks for estimating NO_2 emissions; ii) to generalise the proposed system for detecting anomalous NO_2 emissions involved by environmental pollution in large urban areas.

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References

ARINO, O., SIMON, M., PICCOLINI, I., and ROSAZ., J.M., 2001, The ERS-2 ATSR-2 World Fire Atlas and the ERS-2 ATSR-2 World Burnt Surface Atlas projects. *Proceedings of the 8th ISPRS conference on Physical Measurement and Signatures in Remote Sensing*, Aussois, 8-12 January 2001.

BAILEY, P. 1995, SADIST-2 v100 Products. R-TN-RAL-AT-2164, Rutherford Appleton Lab.

BIANCHINI, M., FRASCONI, P., and GORI, M., 1995, Learning without local minima in radial basis function networks. *IEEE Transactions on Neural Networks*, **6**, 213-220.

BROOMHEAD, D.S., and LOWE, D., 1988, Multivariate functional interpolation and adaptive networks. *Complex Syst.*, **2**, 321-355.

BRUZZONE, L., and FERNÁNDEZ PRIETO, D., 1999, A technique for the selection of kernel-function parameters in RBF neural networks for classification of remote-sensing images. *IEEE Transaction on Geoscience and Remote Sensing,* **37**, 1-6.

CASADIO, S., ZEHNER, C., COLAGRANDE, P., and BUONGIORNO, A., 1999, GOME NO_2 and ATSR temperature data analysis: a hint to the role of biomass burning in trace gasses concentration variations, *European Symposium on Atmospheric Measurements from Space, ESTEC*, Noordwijk, the Netherlands, 18-22 January 1999, ESA WPP-161, **1**, 361-368.

GOME (Global Ozone Monitoring Experiment) Users Manual, 1995, ESA, ESTEC Publishing Division, ESA-SP-1182, European Space Agency.

HATMAN, E.J., KEELER, J.D., and KOWALSI, J.M., 1990, Layered Neural networks with Gaussian hidden units as universal approximations. *Neural Computation*, **2**, 210-215.

http://earth.esa.int/gome_report99

http://shark1.esrin.esa.it/FIRE/AF/ATSR/

LEUE, C., WAGNER, T., WENIG, M., PLATT, U., and JÄHNE, B., 1999, Determination of the Tropospheric NOx Source Strength from GOME Data. ESAMS'99 - *European Symposium on Atmospheric Measurements from Space, ESTEC*, Noordwijk, the Netherlands, 18-22 January 1999, ESA WPP-161, **1**, 385-389.

MOODY, J., and DARKEN, C.J., 1989, Fast learning in networks of locally-tuned processing units. *Neural Computation*, **1**, 281-294.

PARK, J., and SANDBERG, I.W., 1991, Universal approximation using radial basis function networks. *Neural Computation*, **3**, 246-257.

POWELL, M.J.D., 1987, Radial Basis Functions for multivariate interpolation: a review. In Algorithm for approximation, edited by J.C.Mason, M.G. Cox, (Oxford: Clarendon), pp. 143-167.

SHARAN, M., YADAV, A. K., SINGH, M. P., AGARWAL, P., and NIGAM, S.,1996, A mathematical model for the dispersion of air pollutants in low wind conditions. *Atmos. Environ*., **30**, 1209-1220.

TROPOSAT - The Use and Usability of Satellite Data for Tropospheric Research. *EUROTRAC-2 Annual Report* 2000.

ZEHNER C., CASADIO, S., COLAGRANDE, P., and BUONGIORNO, A., 1999, Monitoring of air pollution (emissions of nitrogen dioxide) by ERS-2. *Acts of the 3ª Conferenza Nazionale ASITA: Informazioni Territoriali e Rischi Ambientali*, **2**, 1287-1292.

FIGURE CAPTIONS

Figure 1. Architecture of the RBF neural network used in the proposed nonlinear approach.

Figure 2. Geographical areas considered for evaluating the effectiveness of the proposed methods (the selected areas are within the rectangles).

Figure 3. Abnormal amounts of NO_2 present in the troposphere versus the Julian day. The values $F\left(x_j^{GOME}\right)$ are also reported (see red marks) (Africa Coast region).

Figure 4. Amount of NO_2 emissions produced by biomass burning versus the date: values estimated with the linear approach (red line); reference values (black line) (Africa Coast region).

TABLE CAPTIONS

Table 1. Description of the training and test sets for the five considered geographical areas.

Table 2. Minimum and maximum NO_2 concentration values affecting the considered geographical areas in the studied period.

Table 3. Percentage errors provided by the linear approach in estimating NO_2 produced by biomass-burning in the five considered geographical areas. The estimates of the α coefficient are also given.

Table 4. Overall percentage errors provided by the linear approach in estimating NO_2 emissions produced by biomass-burning. The results are obtained by jointly applying the linear method to all the considered geographical areas.

Table 5. Percentage errors provided by the nonlinear approach in estimating NO_2 emissions produced by biomass-burning on the test sets related to the different geographical areas analysed (errors incurred with different neural architectures are reported). Results are yielded by considering a training set composed of samples related to all the five sites.

Table 6. Percentage errors provided by the nonlinear approach in estimating NO_2 emissions produced by biomass-burning on the test sets related to the different geographical areas analysed (errors incurred with different neural architectures are reported). Results are yielded by defining training and test sets with the leaving-one out method.

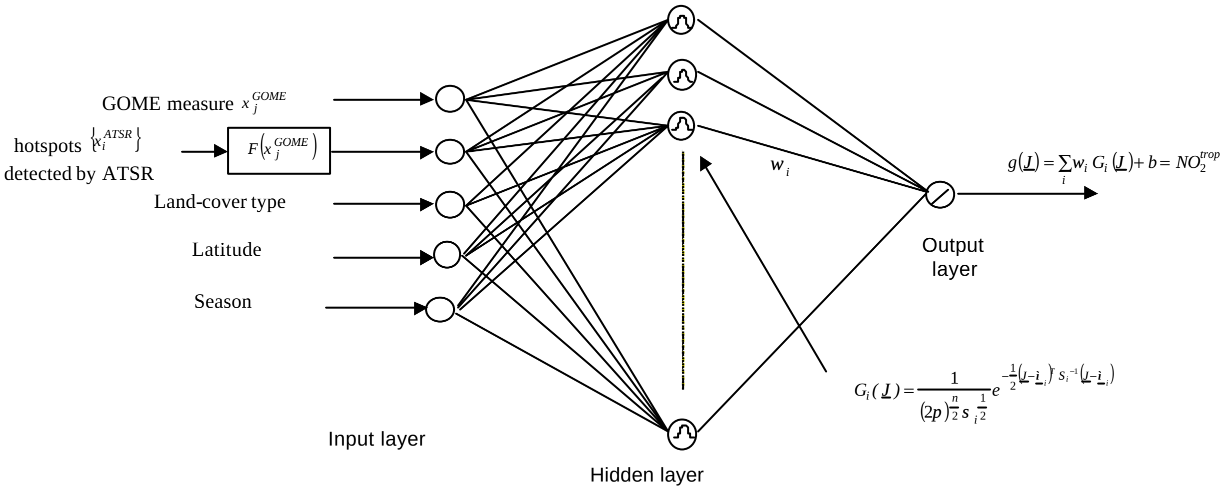

Figure 1

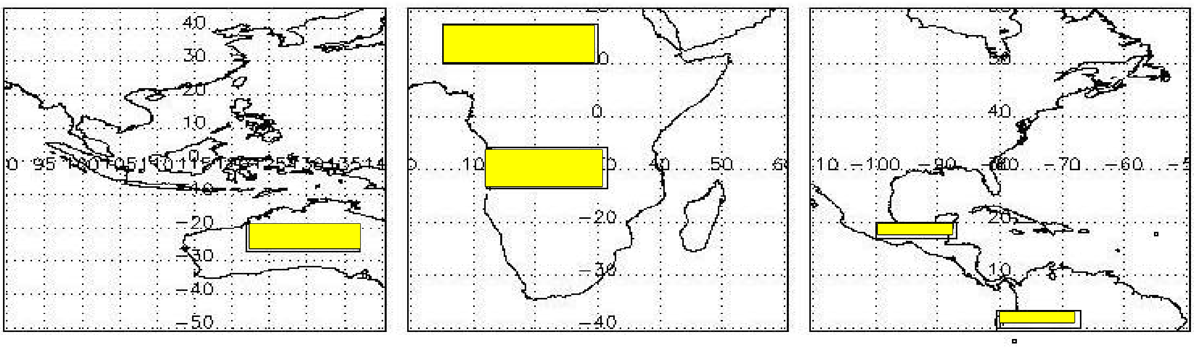

Figure 2

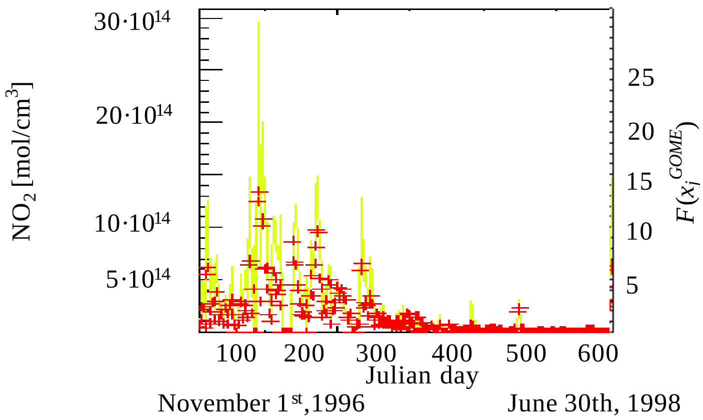

Figure 3

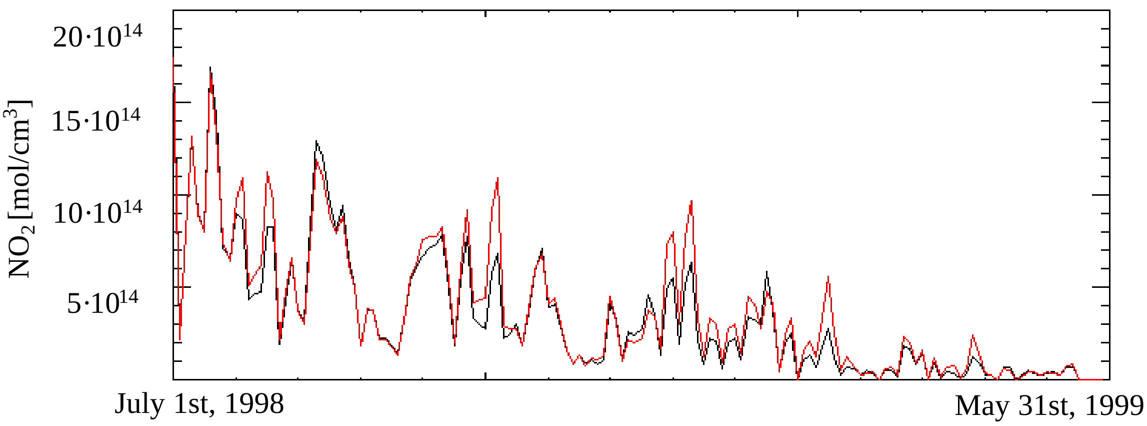

Figure 4

Table 1

Geographical area	Number of patterns	
	Training set	Test set
Africa-coast	5298	2794
Australia	6840	913
Congo	5310	381
Mexico	7283	992
North Brazil	8013	116

Table 2

Geographical area	NO_2 concentration values [10^{14} mol/cm^3]	
	Minimum	Maximum
Africa-coast	0.031	35.889
Australia	0.007	35.889
Congo	0.002	50.657
Mexico	0.002	36.803
North Brazil	0.037	20.437
Global	0.002	50.657

Table 3

Geographical area	Error (%)	Estimated α coefficient
Africa-coast	18.8	6.0
Australia	29.3	16.7
Congo	43.6	8.0
Mexico	35.7	8.0
North Brazil	9.2	5.0
Overall	25.5	-

Table 4

Overall error (%)	Estimated α coefficient
41.9	10.7

Table 5

Number of hidden neurons	Error (%)				
	Africa Coast	Australia	Congo	Mexico	North Brazil
100	12.5	13.5	38.8	14.2	20.1
125	11.7	12.8	39.3	14.2	18.8
150	11.5	11.9	39.3	13.8	18.9
175	11.8	11.9	41.1	14.1	19.0

Table 6

Number of hidden neurons	Error (%)				
	Africa Coast	Australia	Congo	Mexico	North Brazil
100	19.1	11.4	36.5	18.3	26.7
125	18.5	12.8	34.3	16.8	26.5
150	18.7	12.8	35.7	17.8	26.1
175	18.0	12.9	34.0	18.3	26.0