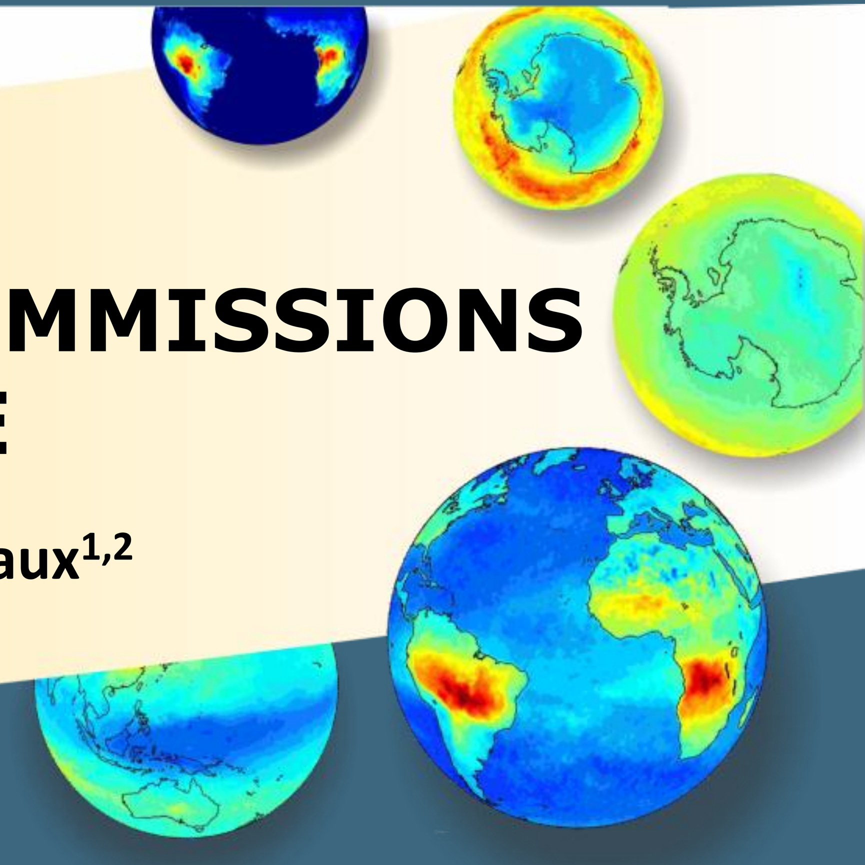

A NEURAL NETWORK APPROACH TO DISCRIMINATE NH3 EMMISSIONS FROM BIOMASS BURNING AND AGRICULTURE

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1- INTRODUCTION

Ammonia (NH3) emission is one of the greatest environmental concerns, undermining agricultural and ecological sustainability worldwide. Satellite monitoring of NH3 from space can improve our understanding of the global nitrogen cycle and recently IASI has shown its ability to monitor NH_3 global distributions and trends at high temporal and spatial resolution.

While livestock wastes and fertilization of crops contributes to more than 50% of the global emission of NH3, biomass burning alone contributes up to 13%.
To allow studying the principal factors driving NH3 emissions from the agricultural sector, it is first necessary to remove the biomass burning contribution from the IASI NH3 total column global dataset **(figure 5a).**
Fire counts, which are not representative for the amount of trace gas emitted and do not account for transport, are of limited use for this purpose **(figure 1**).

Figure 1: True-color image of a fire scene in California (26th October 2003) with the MODIS fire pixels shown in red

2 - THE ARTIFICIAL NEURAL NETWORK (ANN)

In this study a non-parametric method, namely a feedforward-backpropagation artificial neural network (**ANN**), has been developed to separate NH3 total columns from biomass burnings and from other sectors, in particular agriculture.

What is an ANN?

An ANN is a potential tool for data analysis. Is a set of simple computational units (**figure 2**) that are highly interconnected and that attempts to model the capabilities of human brain such as:

- Recognize patterns in the presence of noise;
- Make inferences based on past experiences and relate them to situations that have never been encountered before.

How does the ANN work?

Given a set of input patterns observations with associated known outputs (responses) the objective is to **train** the network to estimate the functional relationship between the inputs and outputs . The trained network can then be used to model or predict a response corresponding to a new input pattern.

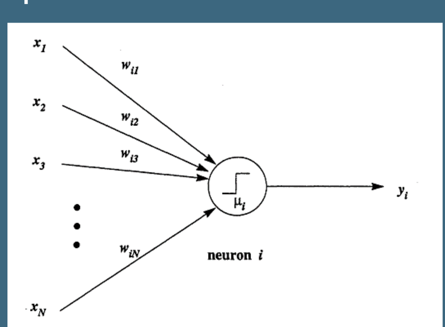

Figure 2: ANN unit (neuron)

$$y_i = \Theta\left(\sum_j w_{ij} x_j - \mu_i\right)$$

y=Output;
Θ=Activation function;
ω=Weights;
x=Input;
μ=Threshold;

ANN training

During the supervised learning (**figure 3**) the neuron receives a weighted sum on inputs from the connected units and outputs a value which will be compared with the known response.
Trough an objective function such as the SSE (sum of square errors) the set of weights connecting the input units to the output units can be optimized and found.

Warner et al. (1996). ***Understanding Neural Networks*** **as Statistical Tools. TAS, vol. 50, N°4.**

3 - METHOD

1- INPUT CONSTRUCTION
Dataset of 60894 observations
(Year 2010)

-IASI NH3 (*molecule of interest*)
-IASI HCOOH (*pyrogenic/ biogenic*)
-IASI CO (*pyrogenic/* anthropogenic).
-GOME2 NO2 (*anthropogenic/* pyrogenic)
-MODIS NDVI (*vegetation type, seasonnality*)

2- TARGET CONSTRUCTION

Two classes defined (pyrogenic and non-pyrogenic) using:
- MODIS Fire product;
- Conditions on NH3, HCOOH, CO, NO2 abundances;

3- ANN TRAINING/ CREATION

- Two layer feedforward ANN;
- Supervised learning training;
- Backpropagation algorithm;

4- ANN TEST ON NEW DATA
(Year 2011)

- Verification with MODIS fire product;
- Comparison with fire emissions inventories (GFED3, FINN)

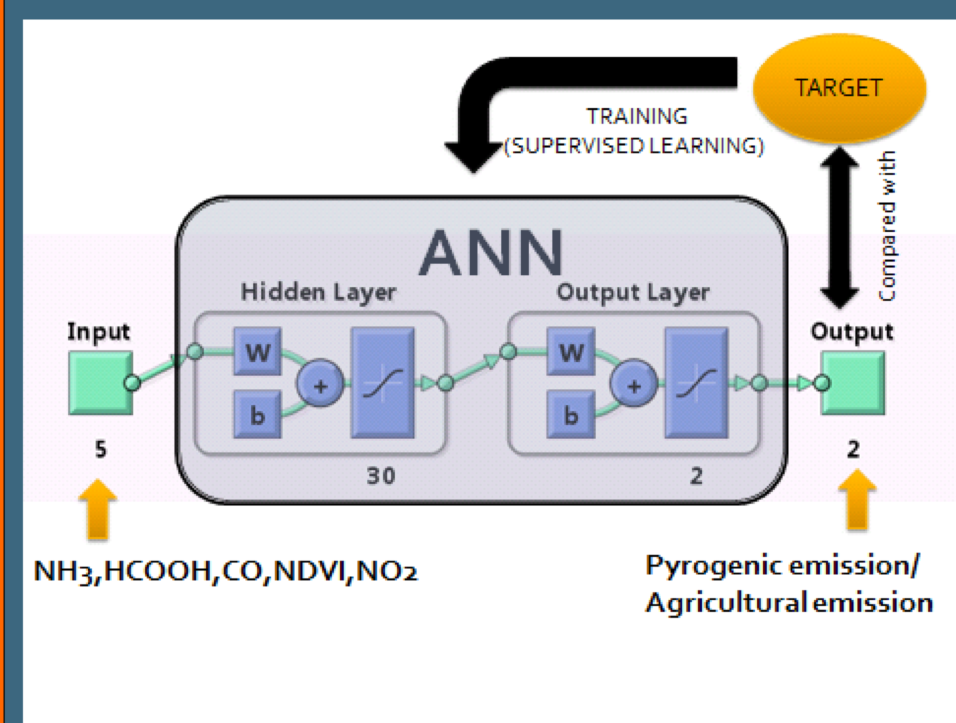

Figure 3: Schematic of the ANN used

4 – RESULTS & CONCLUSIONS

ANN qualitative performance

The figures below show the outputs of the trained ANN associated to new input: one day (**figure 4**, 4388 pixels) and 2 months **(figure 5)** of 2011**.**
In both figures the MODIS fire pixels are displayed in purple to allow fires' localisation and comparison with the ANN's output.
The figures show that the data classified as pyrogenic by the trained ANN matches the MODIS fire data localisation.
The ANN's output < 0.1 was classified as non-pyrogenic and the ANN's output >0.9 was classified as pyrogenic. The outputs with values in between were not classified. The output not classified correspond to approximately ¼ - ½ of the original data.

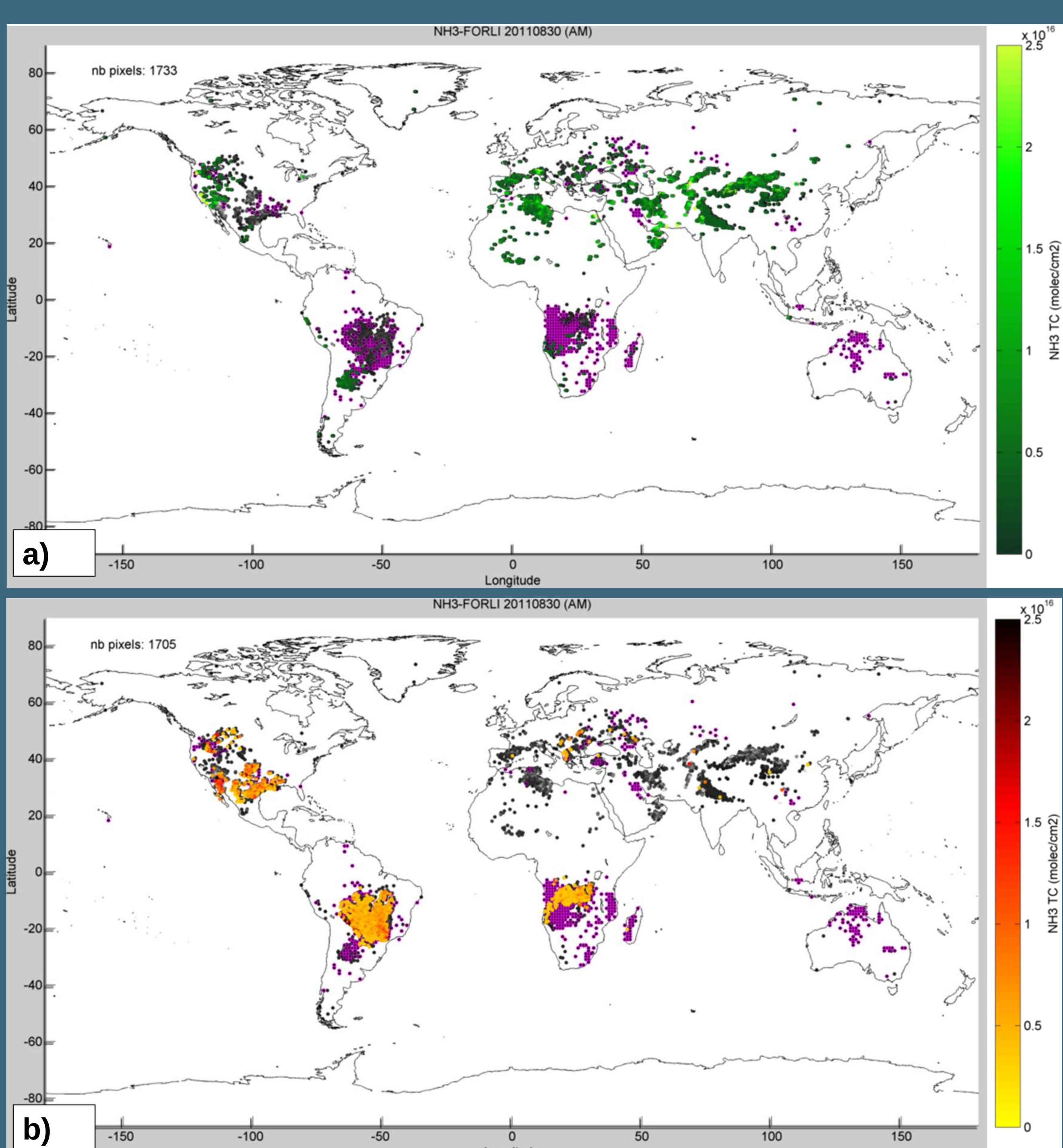

Figure 4: 20110430 NH3 total column (molec/cm2). MODIS fire pixels are superimposed in purple and original NH3 data in grey. a) ANN's non-pyrogenic class (green) b) ANN's pyrogenic class (yellow).

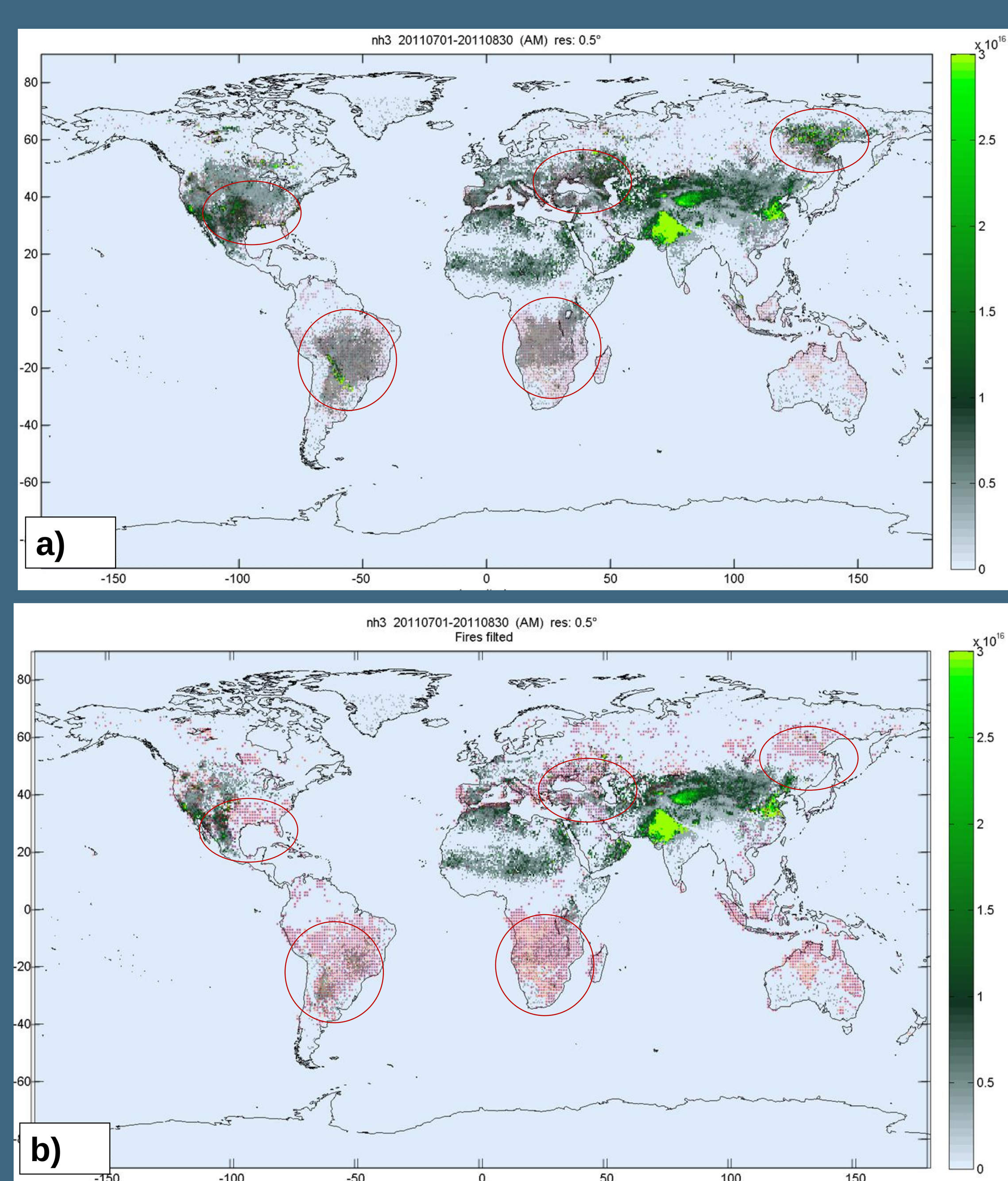

Figure 5: NH3 averaged total column (molec/cm2) from July to August 2011. Gridded MODIS fire data is superimposed in purple. a) Original NH3 data b) ANN's non-pyrogenic output.

ANN quantitative performance: Comparison with Fire Emissions Inventories

When comparing total monthly biomass burning NH3 from GFED3, FINN and the neural network (**figure 6**) one can observe that:

- biomass burning emissions are detected by the neural network with good temporal matching;
- The order of magnitude of the emissions varies over 1-2, FINN estimations being usually the lowest.
- In addition to quantitative differences, there can also be qualitative differences between GFED3 and FINN.

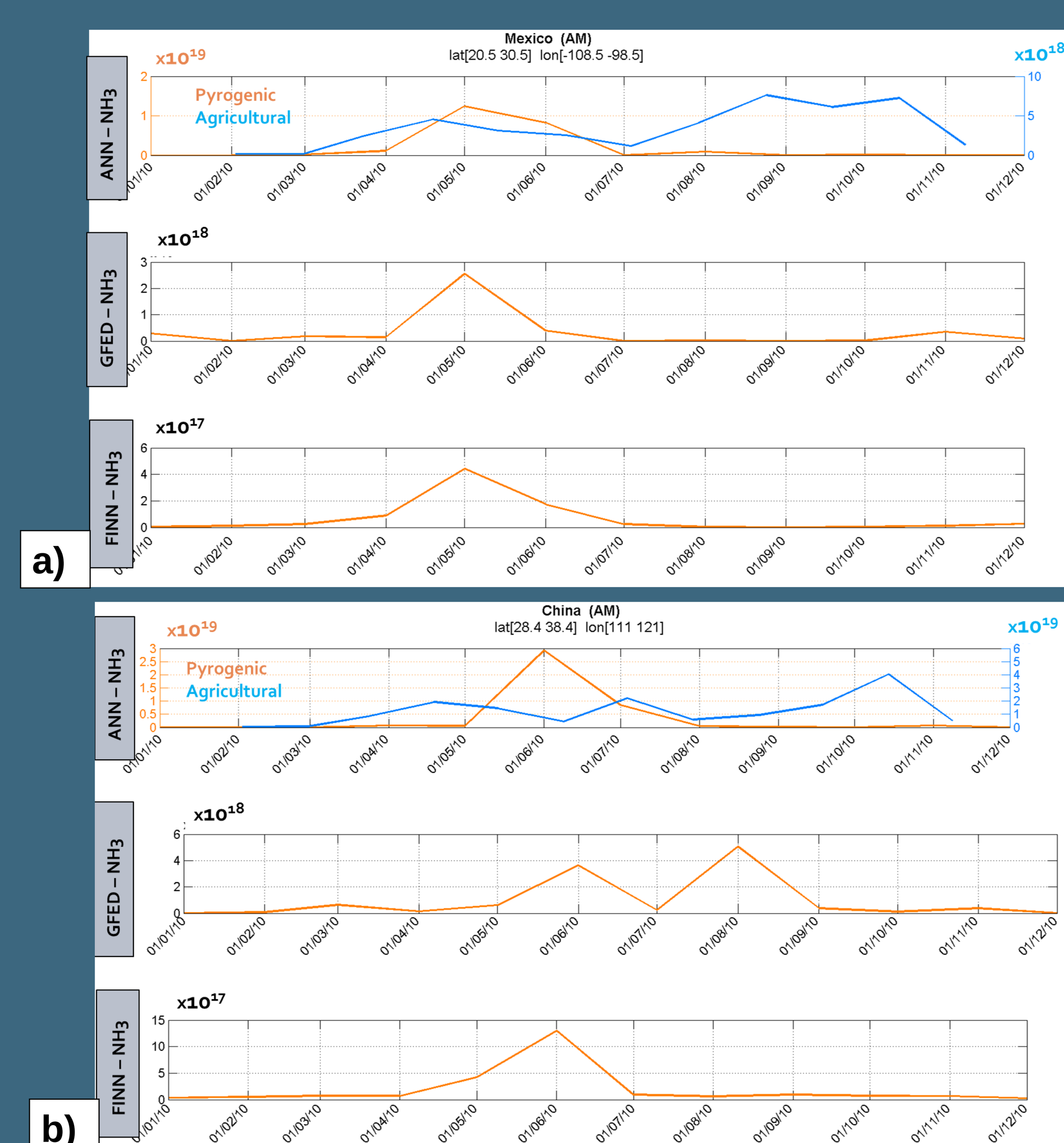

Figure 6: Total monthly NH3 emitted (molec/cm2) time-series for 2010. Top of each figure: ANN's pyrogenic (yellow) and non-pyrogenic (blue) NH3. Middle: GFED3 biomass burning NH3 (molec/cm2). Bottom: FINN biomass burning NH3 (molec/cm2).
a) Mexico b) China.

The artificial neural network developed here uses synergetic measurements of NH3, CO and HCOOH from IASI along with NO2 columns from GOME-2 and NDVI data from MODIS, to detect and isolate biomass burning trace gases. We find that it performs well spatially (plume location) and temporally (peak emissions). The quantitative accuracy achieved by the ANN in terms of trace gas columns is more difficult to assess given that the GFED3 and FINN emission inventories used as reference already have large differences between them and do not account for transport. The next step in this study will be the use of a Chemical Transport Model to perform a quantitative assessment of the ANN.

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