Spatio-Temporal LSTM Forecasting of Ozone Secondary Events

Luiz Angelo Steffenel[1], Gustavo Rasera[1], Nelson Begue[3], Damaris Kirsch Pinheiro[2], and Hassan Bencherif[3]

[1] Université de Reims Champagne-Ardenne, CReSTIC Laboratory EA 3804, Reims, France
[2] Universidade Federal de Santa Maria, Santa Maria RS, Brazil
[3] Université de La Réunion, LACy Laboratory UMR 8105, Reunion Island, France

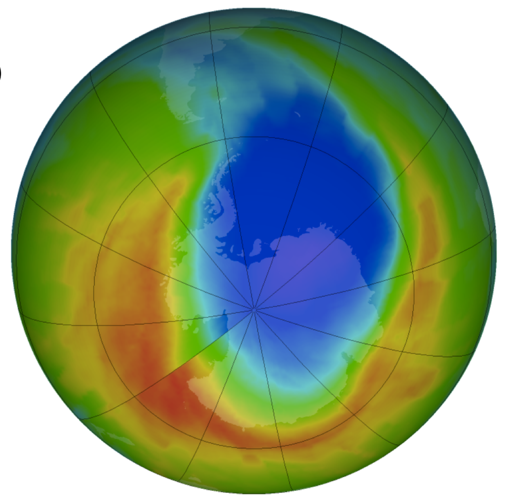
INTRODUCTION

Since its discovery, the "Antarctic ozone hole" has attracted the interest of the scientific community. Given the dynamics of the atmosphere, the ozone hole is accompanied by episodes of exchange between the polar vortex and the mid-latitudes and the tropics [1, 5]. During these events, the polar vortex is deformed and ozone-poor polar air masses move towards mid-latitudes. We call these episodes of isentropic exchanges "Secondary Effects of the Antarctic Ozone Hole" or "Ozone Secondary Effects", for short (OSE). Such episodes may last several days and reach the tropics, causing significant ozone decreases over these areas and potentially increasing the UV radiation levels at the surface [1, 2].

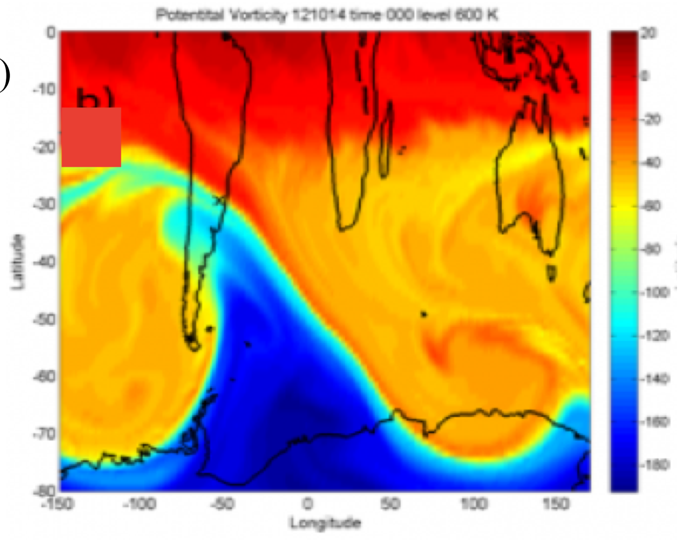
According to UNEP (United Nations Environment Program)[1], a 10% reduction in stratospheric ozone would cause additional 300,000 cases of carcinoma (malignant skin tumors) and 4,500 cases of melanoma (skin cancer) each year, worldwide. The effects on the fauna and flora are also important, with notable risks for the biodiversity and the agriculture.

The secondary effects of the Antarctic Ozone Hole in mid latitude zones are regularly observed over populated zones on South America, south of Africa and New Zealand. Indeed, recent observations reported the occurrence of dozens of OSEs in the last decade over the south of Brazil, resulting in temporary reductions in the total ozone column of more than 10% in densely populated areas. An example is the event from October 10-14, 2012 presented below, which shows the displacement of a polar air mass (in blue) and its extension towards the mid-latitudes to reach the south of Brazil – around 30°S – on figure (a)[2]. Up to 13.7% of reduction in the stratospheric ozone column was observed [6]. Similarly, figure (b) show the potential vorticity (PV) maps obtained by the MIMOSA-Chim high-resolution model [4], showing the movement of a polar air mass (in blue) and its extension towards mid latitudes over South America.

a)



b)



In spite of an associated stratospheric dynamic, there are few studies concerning the numeric modeling of the circulation dynamic of the ozone layer [5]. Indeed, most of the climatic models are limited to the lower atmosphere layers (especially those associated to the weather forecast), and do not explore the interactions in higher layers, like those associated to the Ozone layer.

1 https://www.who.int/uv/publications/globalindex/en/
2 https://ozonewatch.gsfc.nasa.gov/

OBJECTIVES

In this work we examine the interest of using Deep Learning techniques (more specifically, Long Short-Term Memory recurrent neural networks) to forecast OSE events. For this experience, we selected the PredRNN++ model proposed by Wang et al. [7], which has been successfully applied to the analysis of video images. In our study, however, the input data is composed by historical data for the Total Column of Ozone (TCO), obtained by satellites.

This is a first experiment towards the use of Artificial Intelligence in the detection and prediction of OSE. We aim at using the resulting forecasts to detect, monitor and classify OSE by isentropic levels, latitudinal bands and geographical areas.

METHODOLOGY

Predicting the shape and movement of atmospheric events is a real challenge of predictive learning. Contrarily to some datasets studied by [7], atmospheric phenomena are not rigid, their speeds and trajectories vary, and their shapes may accumulate, dissipate or change rapidly due to the complex atmospheric environment. Furthermore, Ozone datasets are usually provided in a daily basis, making the tracking of the air masses even more complex. Hence, being able to model the spatial deformation of the Ozone concentration is a key aspect for the prediction of OSE events.

In this work we used part of the Multi Sensor Re-analysis (MSR2) [3] dataset corresponding to the OMI sensor, and covering the period between Jan 1, 2004 to Dec 31, 2018. This dataset is composed of daily measures of the Total Column Ozone (TCO) in Dobson units.

We preprocessed this dataset in order to highlight only the OSE occurrences, using these steps:

1. For a given day k, compute $mean_k$, the average TCO for the precedent 15 days
2. Compute the variation between mean of the previous days and the observation for day k
$$\Delta_k = -(TCO_k - mean_k) \times 100 / mean_k$$
3. Retain only the measures that show more than 10% of reduction
$$OSE = \begin{cases} \Delta_k \ if \geq 10\% \\ 0 \ otherwise \end{cases}$$

We chose to observe the mean of a moving time window as it is more adapted to capture the seasonal fluctuations than the simple historical month mean. Also, we chose to represent the TCO variation instead of the raw Dobson values to highlight the events, simplifying the learning task. In addition, the main harm of OSE happens during the days following the sudden drop of the Ozone concentration. After a few days, even if the TCO concentration remains low, the population will probably be warned by the governmental health agencies to take the required actions (use sunscreen, hats, avoid exposition at given hours, etc.).

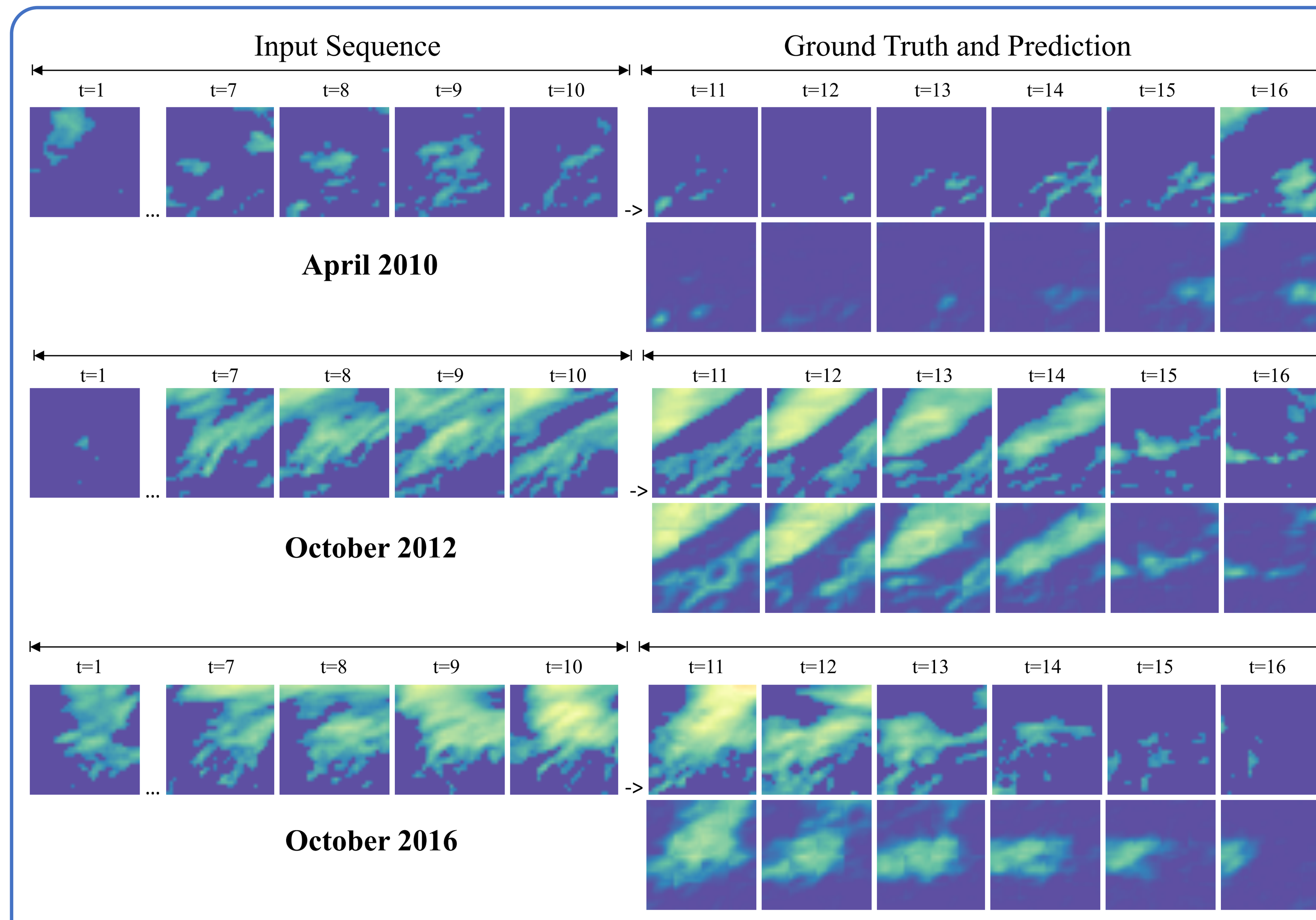
Due to our previous works on OSE, we focus the experiment in the zone surrounding the Southern Spatial Observatory in Brazil (*Observatório Espacial do Sul – OES/CRS/INPE – MCTI*), located at 29.4°S; 53.8° W; 488.7 m). Hence, we selected a 32° × 32° grid centered at these coordinates.

These values were mapped as pixels in a 32 × 32 gray-scale images, each pixel with a value between 0 and 1 (0 to 100% variation). For each day in the dataset, we define a sequence consisting of 20 frames, 10 for the input (the previous 10 days), and 10 for the output (forecasting).

The total 5,075 sequences are split into a training set of 3,998 samples and a test set of 1,077 samples. We trained the PredRNN++ model [7] over 10,000 iterations. After prediction, we transform the resulted intensities into colored maps. These predictions are compared with the real observations (ground truth).

RESULTS

A qualitative comparison of the predicted sequences is given in the next column. Three different periods are represented. Both October 2012 and October 2016 are known OSE occurrences. The case of April 2010, it was chosen as a "control" period as in this season air masses are rarely originated from the pole, and Ozone variations are mostly due to the influx of equatorial masses whose Ozone concentration is normally reduced.



CONCLUSIONS

This preliminary work gives us some insights on the efficiency and precision of Deep Learning forecasts for Ozone Secondary Effects. The obtained results are encouraging as we were able to obtain some predictions with similar forms and intensities than the observed events. However, the results are not always precise, and the quality of the forecast easily degrade for long term predictions, requiring therefore an additional work on the learning algorithms and datasets.

This work also helped us to improve data extraction and feature selection techniques, and to understand the impact of different parameters such as the number and size of hidden convolution layers. Hence, we shall continue to investigate how to better tune the Deep Learning network, as well as trying other algorithms adapted from the video frame.

REFERENCES

1. Bencherif H., et al.: Examination of the 2002 major warming in the southern hemisphere using ground-based and Odin/SMR assimilated data: stratospheric ozone distributions and tropic/mid-latitude exchange, Can. J. Phys., 85, 1287-1300, 2007
2. Casiccia C., et al..: Erythemal irradiance at the Magellan's region and Antarctic ozone hole 1999-2005, Atmosfera, 21, 1-12, 2008
3. Eskes, H. et al.: Assimilation of GOME total ozone satellite observations in a three-dimensional tracer transport model, Q.J.R.Meteorol.Soc. 129, 1663-1681, 2003.
4. Hauchecorne A., et al.: Quantification of the transport of chemical constituents from the polar vortex to midlatitudes in the lower stratosphere using the high-resolution advection model MIMOSA and effective diffusivity, J.Geophys. Res.,107(D20), 8289, 2002.
5. Marchand M., et al.: Model simulations of the impact of the 2002 Antarctic ozone hole on midlatitudes. J. Atmos. Sci., v. 62, p. 871–884. doi:10.1175/JAS-3326.1, 2005
6. Peres, L. et al.: Measurements of the total ozone column using a Brewer spectrophotometer and TOMS and OMI satellite instruments over the Southern Space Observatory in Brazil, Ann. Geophys., 35, 25-37, 2007
7. Yunbo W., et al.: PredRNN++: Towards A Resolution of the Deep-in-Time Dilemma in Spatiotemporal Predictive Learning, International Conference in Machine Learning, 2018

ACKNOWLEDGEMENT

This research has been supported by the French-Brazilian CAPES-COFECUB MESO project (2017-2020). We would like to thank all the partners, financing agencies and the ROMEO Supercomputing Center for their support and resources.

EGU General Assembly 2019, Vienna, Austria, 7-12 April 2019
https://meetingorganizer.copernicus.org/EGU2019/EGU2019-8075.pdf