Forecasting ionospheric Total Electron Content maps with deep neural networks

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DeLTA : Deep Learning for Aerospace Applications

Electromagnetism

Remote sensing

Optics

Robotics

Materials and structures

Fluid mecanics

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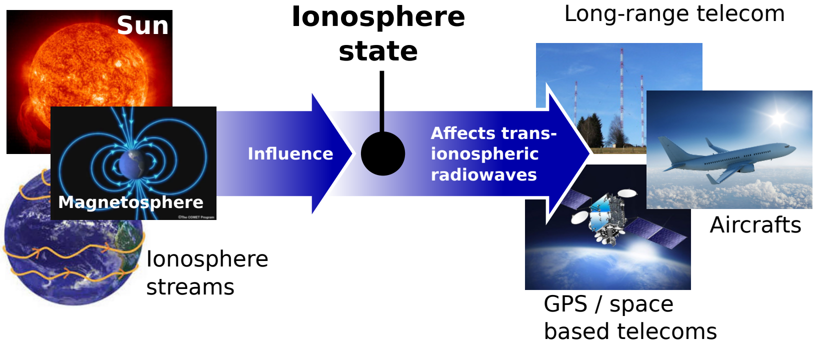
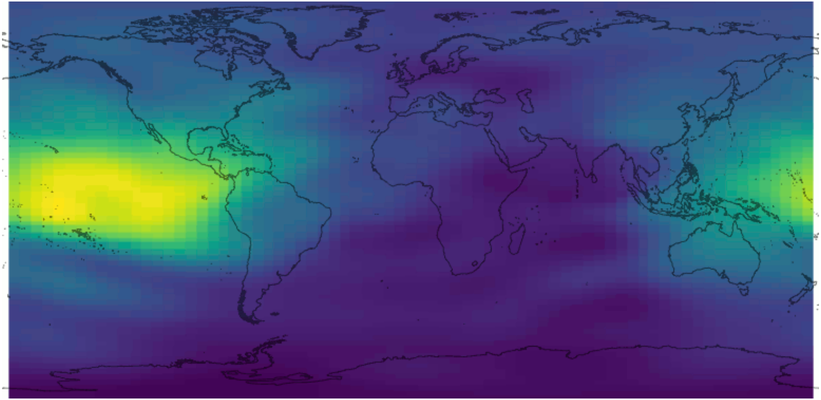
Ionosphere

Ionosphere

Highly ionized region in upper atmosphere.



TEC Map



Total Electron Content (TEC) measuresionospheric activity.

TEC = Integration of electron density along a $1m^2$ sect. tube between GNSS station and GNSS satellite

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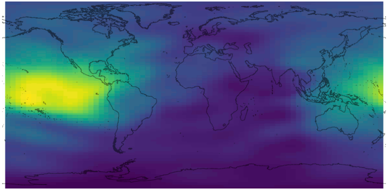
Data



Code TEC data

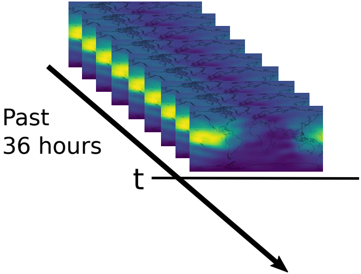
aiuws.unibe.ch/ionosphere/
based 200 stations
1 TEC map every 2 hours since 2003

- 72×80
- Resolution : $5^\circ \times 2.5^\circ$

Approach

Preprocessing

Heliocentric coordinates : remove rotation effect.



Approach

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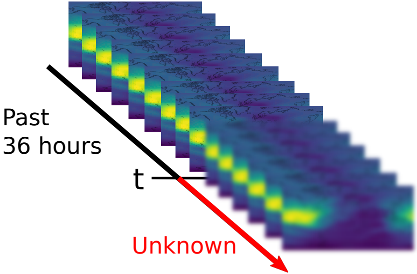

Approach

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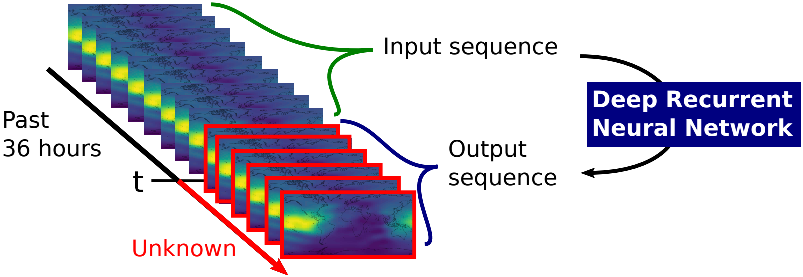
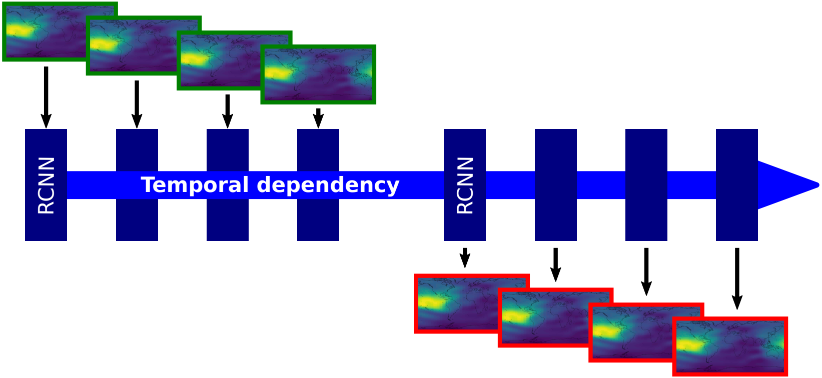
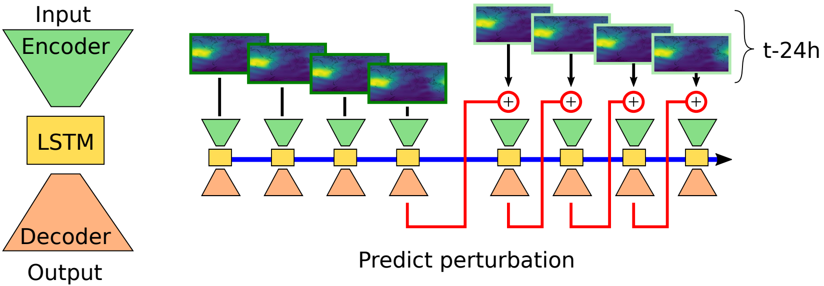


Network architecture

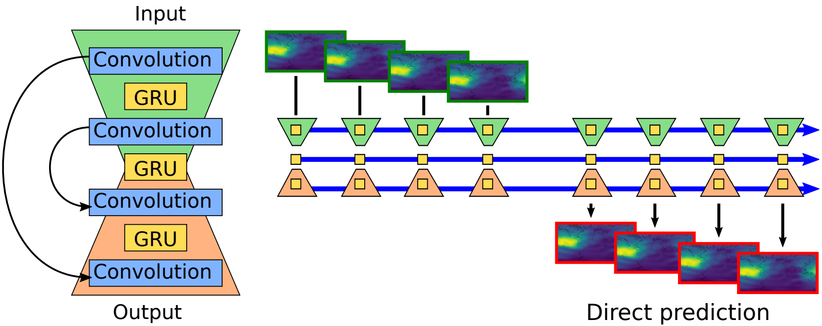


Encoder - Decoder architecture [1]



1. Work presented at ICONIP : *Deep sequence-to-sequence neural networks for ionospheric activity map prediction* [1]

Recurrent U-net



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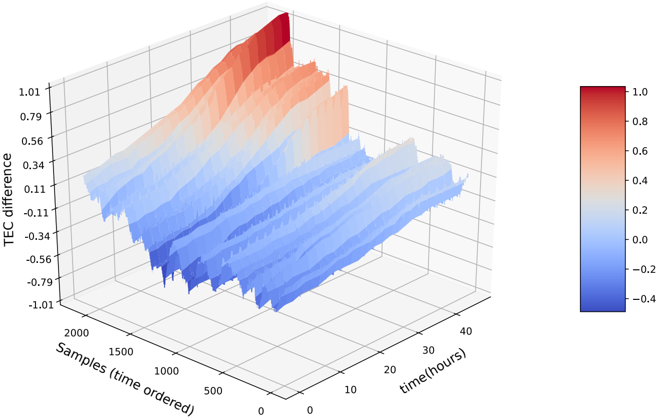
Comparison with Encoder-Decoder method



Prediction difference between [1] and Rec-Unet.

Quantitative results

Whole test set

Method	RMS 48h	First 24h	Last 24h
Priodic	2.74	2.88	**2.53**
ICONIP	**2.65**	2.65	2.65
Ugru	2.66	**2.46**	2.85

First half of test set

Method	RMS 48h	First 24h	Last 24h
Priodic	2.88	2.87	2.89
ICONIP	2.75	2.74	2.76
Ugru	**2.60**	**2.46**	**2.74**

Note : mean over 6 runs, numbers updated compared to paper. Different test set.

Comparison with other approaches

	Reference	RMS (ref)	RMS (best run)
[2]	Chunli D., Jinsong P.	1.45	2.1
[3]	Huang, Z., Yuan, H.	≤ 2	1.53
[4]	Niu, R. *et al.*	3.1	0.73

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2. Erratum : in paper numbers from [1]. Replaced at `aboulch.github.io`

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Conclusion

Our method

- Global TEC prediction
- Recurrent Unet

Perspectives

- Improve prediction from 24h to 48h
- Improve convergence (may diverge)
- Reduce time dependency to training set (train on more data)
- Involve other sources (e.g. sun imagery)

Thanks for your attention

Slides and updated paper at : `aboulch.github.io`

Implementation

- PyTorch framework
- Code to be released

References

Noëlie Cherrier, Thibaut Castaings, and Alexandre Boulch.
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In *International Conference on Neural Information Processing*, pages 545–555. Springer, 2017.

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Z. Huang and H. Yuan.
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Radio Science, 49(4) :283–292, 2014.

R. Niu, C. Guo, Y. Zhang, L. He, and Y. Mao.
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