

A new spatio-temporal graph neural network method for the analysis of GNSS geodetic data

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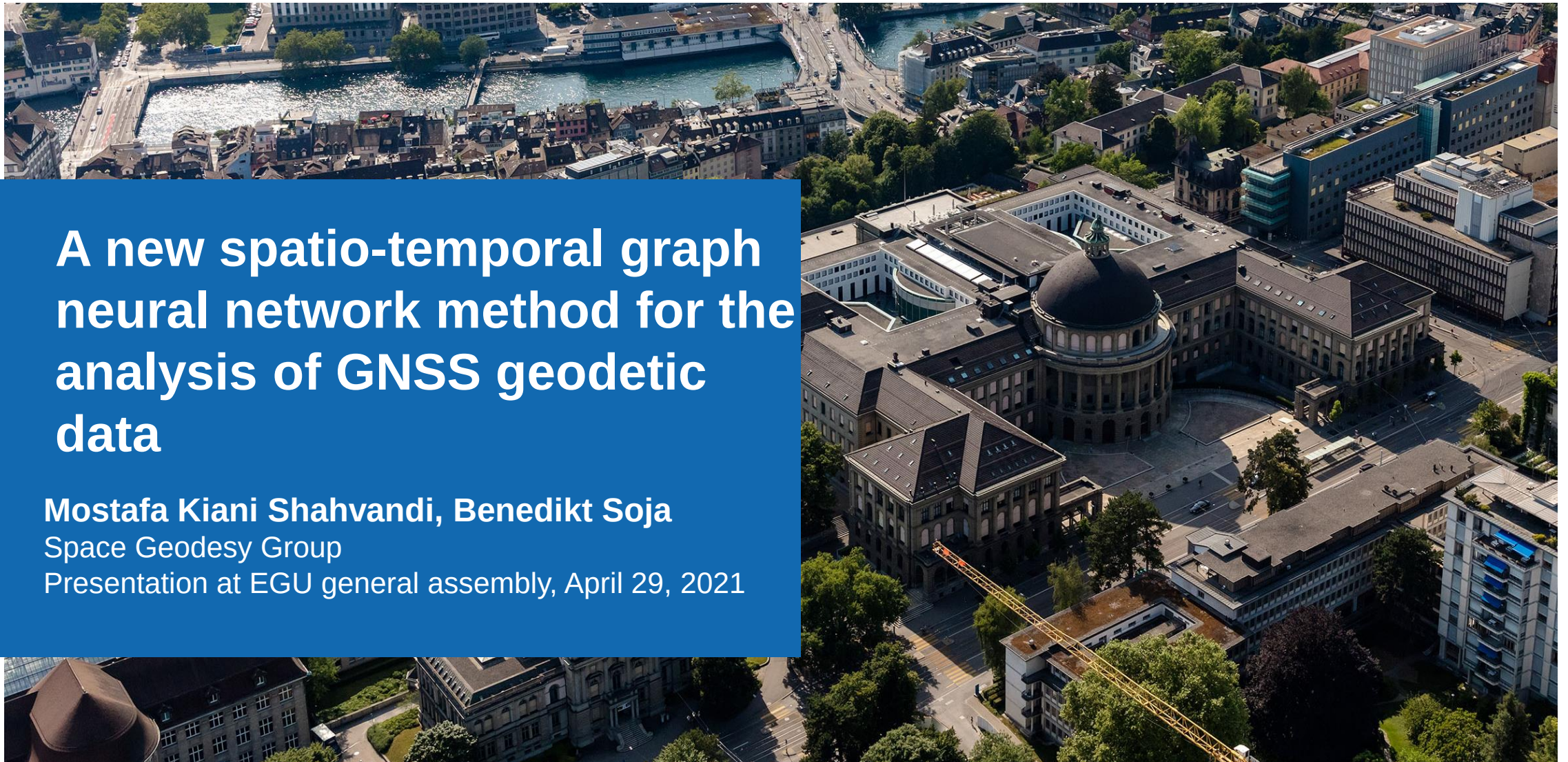
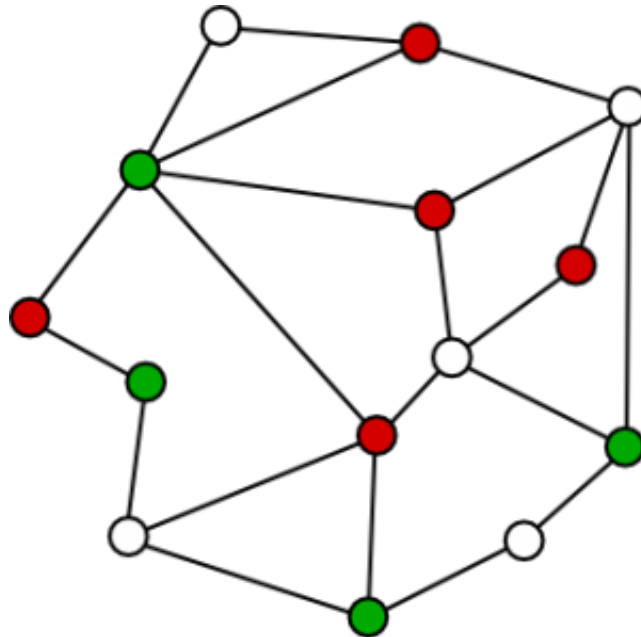


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Introduction to graph neural networks

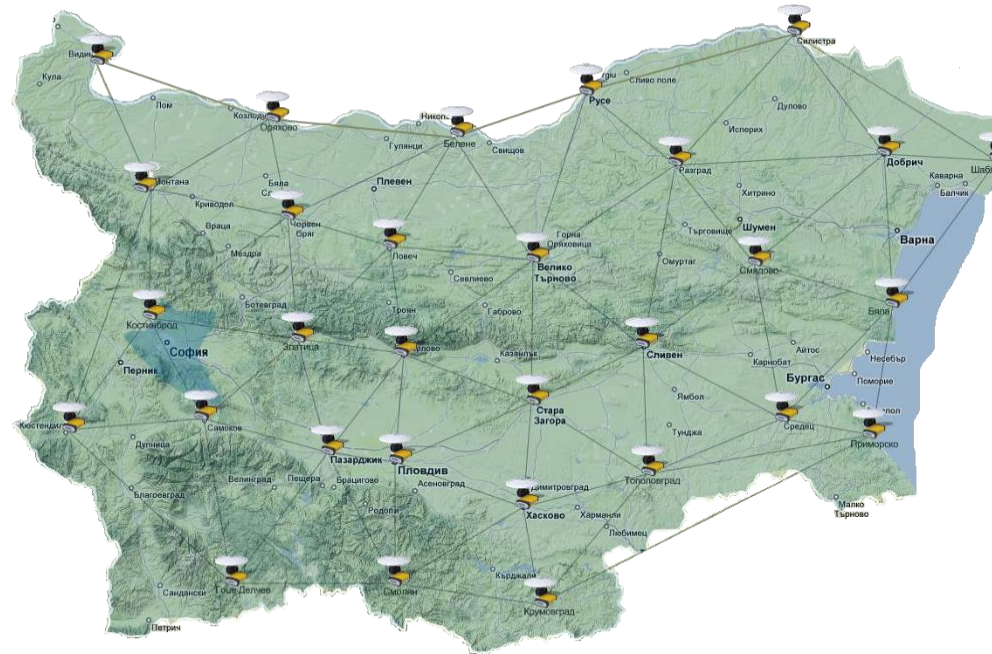
- Graph Neural Networks (GNN) are a newly developed category of machine learning algorithms that are based on relational data
- The relationships between nodes (vertices), as well as between edges are known
- Examples include relation between each person and his/her favorites, road networks and traffic, human skeleton action recognition, natural language processing, chemical bonds between molecules, ...



From open.ac.uk

GNSS networks as graphs

- GNSS networks consist of a series of observing stations
- The stations can be considered as nodes of a graph
- The relationships between different stations can be considered as edges
- Stations that are connected via an edge are called neighbors

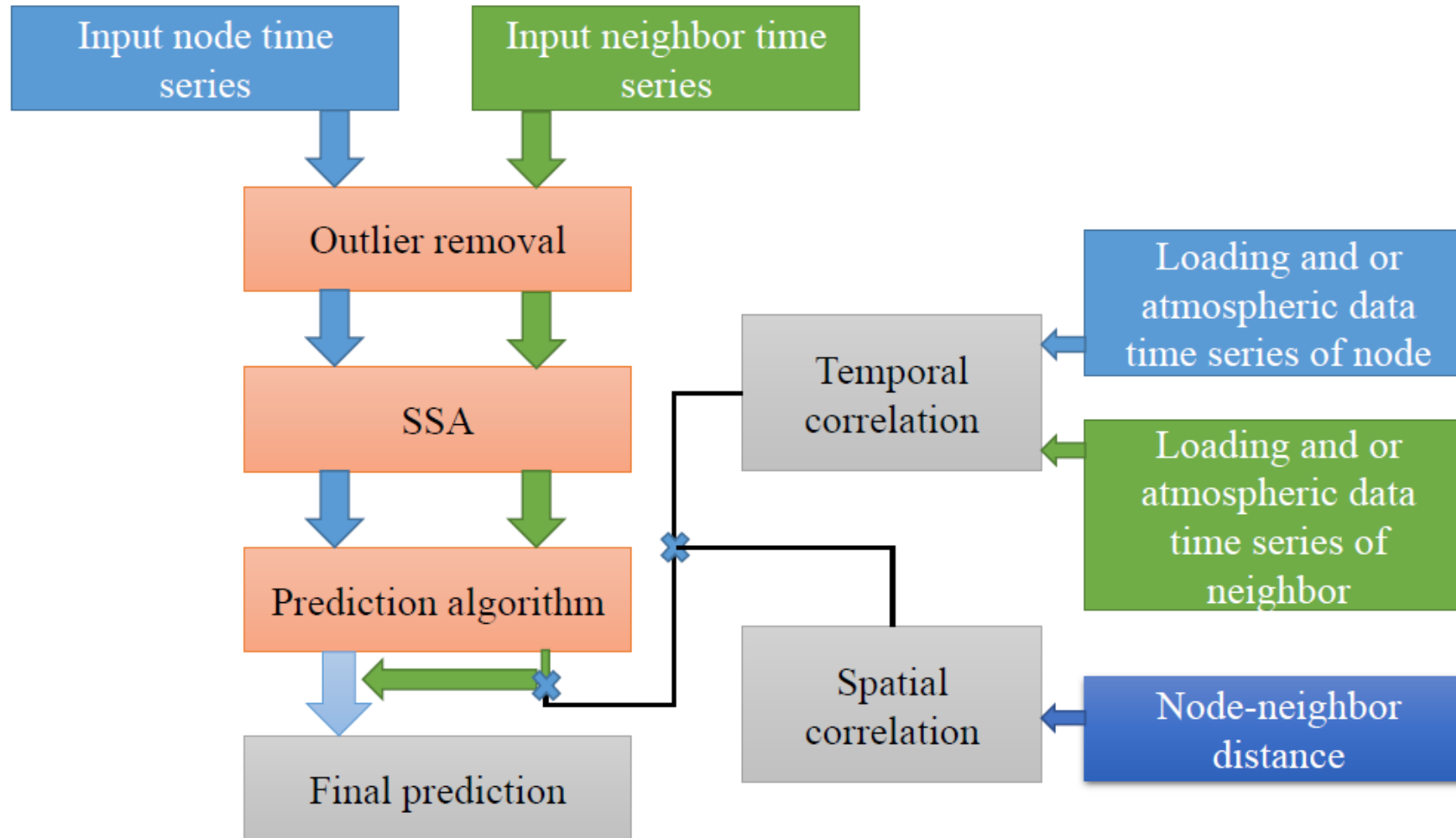


From solitech.bg

Shortcomings of the current methods and the need to devise a new algorithm

- Although the present methods would work well for some applications, they are not powerful enough for the case of the GNSS networks
 - These methods are application oriented, meaning they are not general approximants
 - They present low training and prediction accuracy
 - They are time-consuming, without enough accuracy
 - Not suitable for the time series as input
- Therefore, it seems that a new method of GNN is necessary for the case of GNSS networks
- This method should have the following characteristics
 1. Be based on the unique properties of the GNSS networks, i.e. having a **physical** basis
 2. Be as accurate as possible for the prediction of future epochs of the time series, based on the neural networks-based machine learning algorithms, i.e. having a **mathematical** basis

A new graph neural network method



A new graph neural network method

Mathematical model

1- general (near and far field)

$$y_i = \frac{1}{1 + n(u)e^{-\max(L^2)}} (f(W_i, x_i, t) + \sum_{u \in N(x_i)} c_{ux_i}(t) e^{-d\left(\frac{L(u, x_i)}{L_p}\right)^2} f(W_u, x_u, t) \Big|_{W_i, x_i, t})$$

2- simplified (far field only)

$$y_i = f(W_i, x_i, t) + \sum_{u \in N(x_i)} c_{ux_i}(t) e^{-d\left(\frac{L(u, x_i)}{L_p}\right)^2} f(W_u, x_u, t) \Big|_{W_i, x_i, t}$$

Y_i : prediction, f : activation function + ML method, W_i : i^{th} weight matrix
 x_i : i^{th} node, t : time, $c_{ux_i}(t)$: temporal correlation

$e^{-d\left(\frac{L(u, x_i)}{L_p}\right)^2}$: spatial correlation, $L(u, x_i)$: length between nodes
 L_p : threshold defining neighborhood

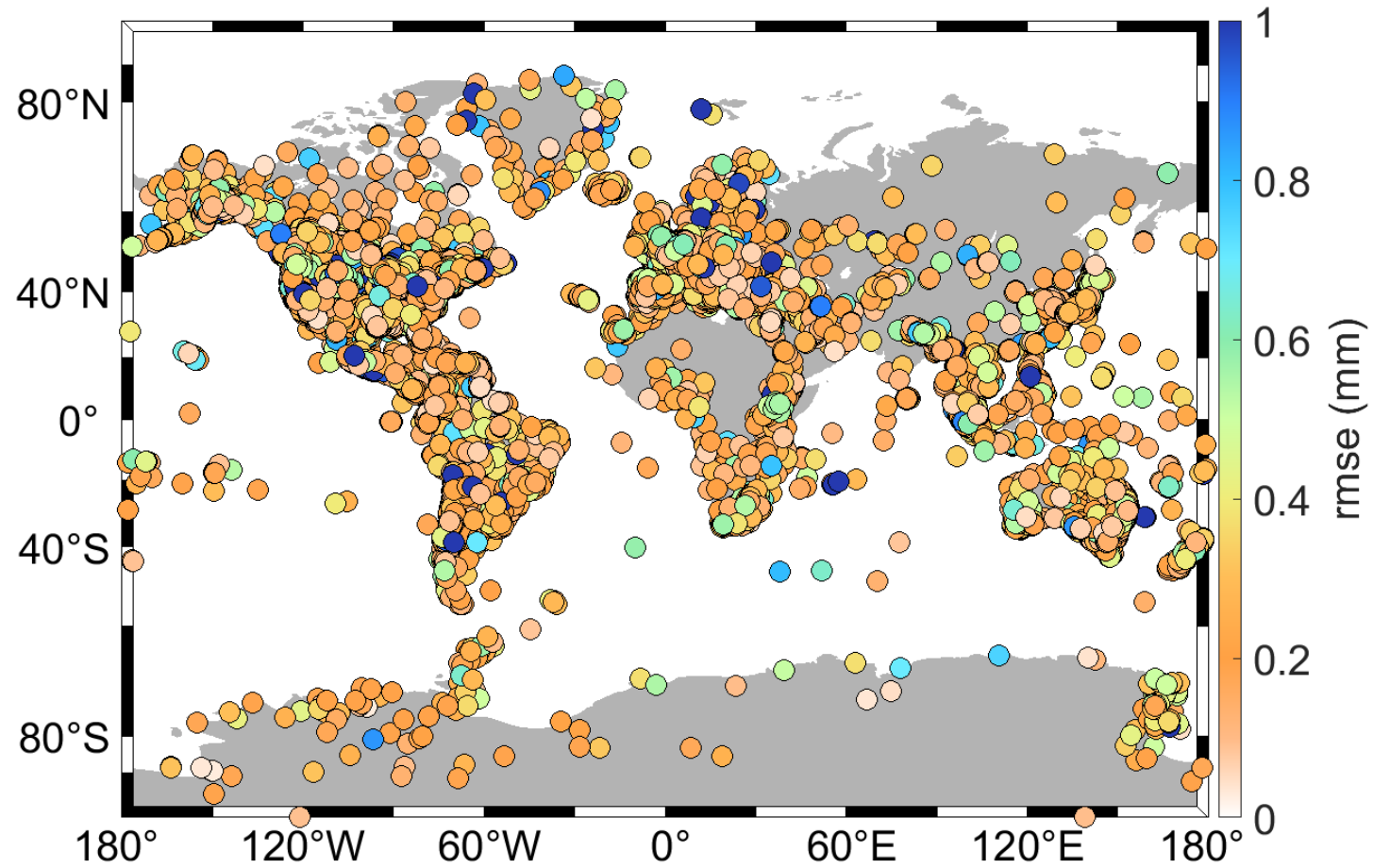
Results on real data

- GNSS coordinate time series represent the change in the earth's surface
- Time series to be analyzed are originally taken from NGL (Nevada Geodetic Laboratory)
- For this study, we only consider the vertical component
- The prediction of coordinates is based on previous values and additional data sets:
 - Geophysical loading data included: NTOL, NTAL, HYDL
 - Weather data from ERA-5 (temperature and humidity)
- Number of time series to be analyzed globally: 18794
- Data splitting: 60% training, 20% validation, 20% test, chosen either randomly or sequentially
- Accuracy assessment based on the values of prediction minus observed
- 10 different machine learning algorithms and 4 different statistical methods
- 4 different performance metrics

Results on real data

Method	Mean RMSE(mm)	Mean sMAPE(%)	Model fitting (%)	Computational Complexity rank
BFFN	0.344	15.829	1.003	6
GP	0.344	16.054	4.903	1
ARIMA	0.407	14.824	8.292	8
Theta	0.426	16.699	13.556	12
SES	0.491	18.491	14.849	13
BL ₁ P	0.536	16.221	8.744	5
HOLT	0.589	19.981	23.135	11
GRNN	0.743	16.237	14.890	9
CART	0.896	16.249	16.801	14
RNN	1.041	17.629	22.022	3
SVRM	2.999	17.998	22.880	2
LSTM	3.328	19.329	30.446	4
CFN	6.615	19.528	32.167	7
PNN	17.952	29.998	65.427	10

Results on real data: example BFFN



Conclusions

- The new method works better than the other state-of-the-art graph neural networks
- Bayesian method is the most accurate method for time series prediction in the graph neural network
- GNSS time series are generally predicted with lower accuracy than those in fields such as economics, using the SMAPE criterion

Additional conclusions

- Random cross validation is better than the standard one
- There is no strong correlation between the number of predictions and the accuracy, as long as the training is performed well
- The more the number of removed eigenvalues in the SSA procedure, the more accurate the predictions will be, in terms of rmse
- GEST is the best method of outlier removal
- Correlation computed by weather data is the best one, compared to the loading models or their combinations
- The same conclusions still hold in a regional scale, such as in Europe

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