Yaroslav Vyklyuk

Bukovinian University, Chernivtsi, Ukraine,

Institute of laser and optoelectronics intelligent manufacturing, Wenzhou University, China,

Milan Radovanovich

Geographical Institute "Jovan Cvijić", Serbian Academy of Sciences and Arts, Belgrade, Serbia,

South Ural State University, Institute of Sports, Tourism and Service, Chelyabinsk, Russia

Slavica Malinović Milićević

University Center for Meteorology and Environmental Modelling, University of Novi Sad, Dr Zorana Djindjića

Deep Learning LSTM Recurrent Neural Network for consequence forecasting of the solar wind disturbance

Content

- **Preliminary analysis of input and target data**
- **Data transformation**
  - Import and consolidation of data
  - Aggregate data to equal sampling rates
  - Filling and interpolation missing data
  - Reduce of task dimension
- **Creation and training of model ensembles**
  - Linear models
  - Artificial Neural Network models
  - LSTM Recurrent Neural Network models
- **Adequacy testing and sensitivity analysis**
- **Examples**
- **Conclusions**

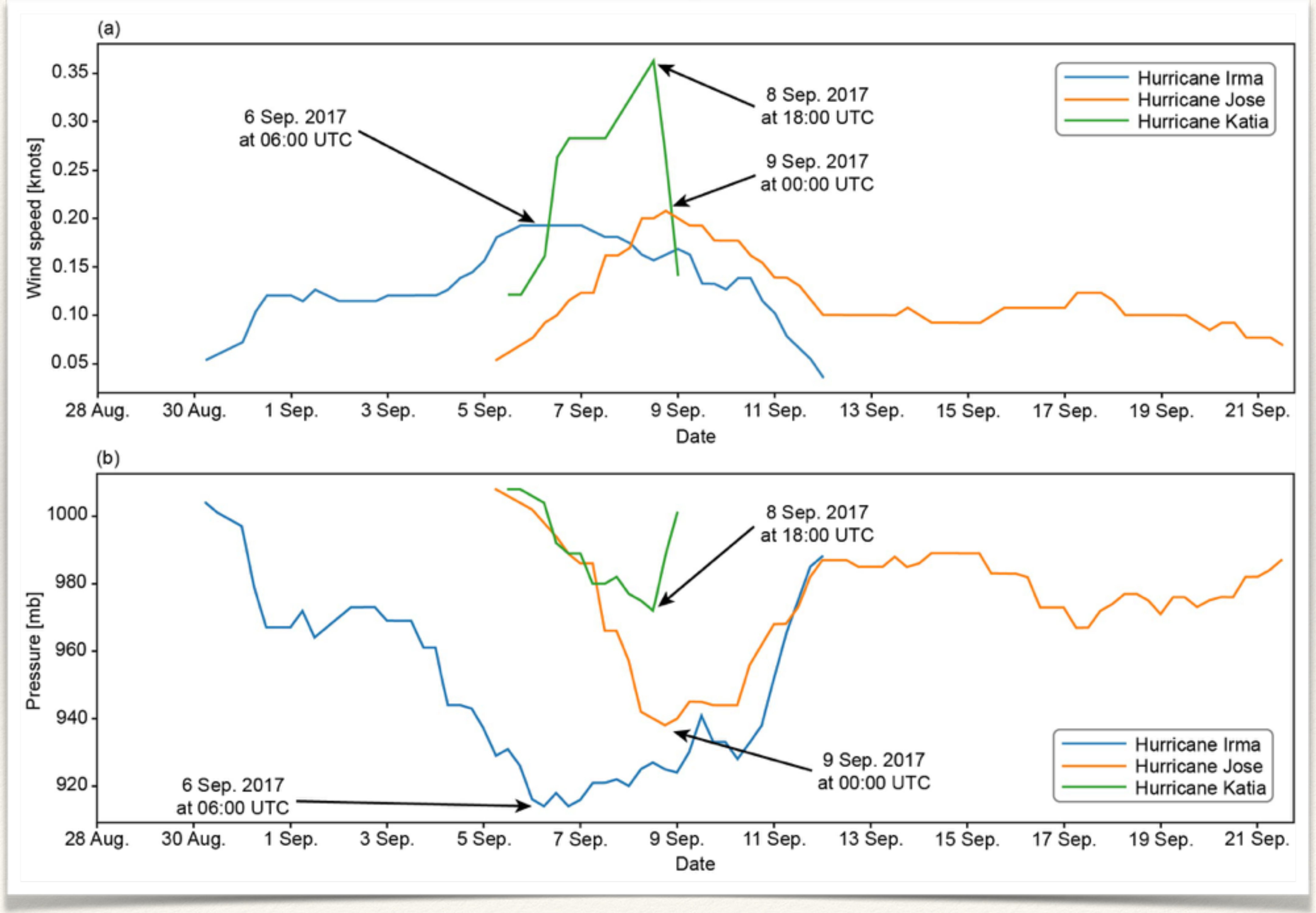
Goal

The task was to find functional dependencies between the parameters of solar wind (SW) and the main characteristics of hurricanes: the speed of wind and pressure.

The main characteristics of the investigated hurricanes

	Irma	Jose	Katia
The beginning	30 Aug. 2017 at 12:00 UTC	5 Sep. 2017 at 12:00 UTC	5 Sep. 2017 at 18:00 UTC
The end	12 Sep. 2017 at 00:00 UTC	21 Sep. 2017 at 18:00 UTC	9 Sep. 2017 at 20:00 UTC
Date of maximum wind speed	6 Sep. 2017 at 6:00 UTC	9 Sep. 2017 at 11:00 UTC	8 Sep. 2017 at 18:00 UTC
Duration	13 days	16 days	4 days
Sampling	6 hr	6 hr	6 hr
Number of observations	52	66	15

Wind speed (a) and pressure (b) for hurricanes Irma, Jose and Katia. Black arrows represent dates of maximum wind speed and air pressure



The main characteristics of the investigated hurricanes

The Unisys was the source of data on the hurricanes Irma, Jose, and Katia.The data included maximum sustained winds in knots, and central pressure in millibar (mb) for the periods of 6 hours (0–6 hr, 6–12 hr, 12–18 hr, and 18–24 hr). The 5-minutes data on solar particle and electron flux (source: GOES-15) were provided by the Space Weather Prediction Center. The particles are protons (P) at > 1 MeV, > 5 MeV, > 10 MeV, > 30 MeV, > 50 MeV, and > 100 MeV. The data on electrons (E) included > 0.8 MeV and > 2.0 MeV. The source of daily solar radio flux at 10.7 cm (2 800 MHz) was Space Weather Prediction Center.The data on proton speed (km/s) and proton density (protons per cubic centimetre) were obtained from data archive of the SOHO CELIAS Proton Monitor.

Characteristics of the set of SW

Frame	The characteristics of solar activity	Units of measurement	The beginning	The end	Sampling
1	P > 1, P > 5, P >10, P > 30, P > 50, and P > 100	Protons (> MeV)/($cm^2 \cdot s$)	28 Aug. 2017 at 00:00 UTC	22 Sep. 2017 at 00:00 UTC	5 min
2	E > 0.8 and E > 2.0	Electrons (> MeV)/($cm^2 \cdot s$)	28 Aug. 2017 at 00:00 UTC	22 Sep. 2017 at 00:00 UTC	5 min
3	Radio Flux 10.7		28 Aug. 2017 at 00:00 UTC	21 Sep. 2017 at 00:00 UTC	1 day
4	Proton speed	km/s	28 Aug. 2017 at 00:00 UTC	22 Sep. 2017 at 00:00 UTC	1 hour
5	Proton density	Protons/cm^3	28 Aug. 2017 at 00:00 UTC	22 Sep. 2017 at 00:00 UTC	1 hour

Import and consolidation of data

$$DF_f = (Key = Date\&Time: Data =< Field_{f1}, \dots, Filed_{fn} >) \quad (1)$$

where f – frame number from Table 1, $Field_{fi}$ – i-th field of Frame f.

ADV	LAT	LON	TIME	WIND	PR	STAT
1	16.4	-30.3	08/30/12Z	45	1004	TROPICAL STOR
2	16.4	-31.2	08/30/18Z	50	1001	TROPICAL STOR
3	16.4	-32.2	08/31/00Z	55	999	TROPICAL STOR
4	16.5	-32.9	[illegible]	60	997	TROPICAL STOR

ADV	LAT	LON	TIME	WIND	PR	STAT
1	12.3	-39.1	09/05/12Z	35	1008	TROPICAL
2	12.5	-40.6	09/05/18Z	40	1006	TROPICAL
3	12.3	-41.7	09/06/00Z	45	1004	TROPICAL
4	12.5	-42.8	09/06/06Z	50	1002	TROPICAL
5	13.1	-44.5	09/06/12Z	60	998	TROPICAL

ADV	LAT	LON	TIME	WIND	PR	STAT
1	22.4	-96.7	09/05/18Z	30	1008	TROPICAL DEPRESSION
2	22.2	-96.4	09/06/00Z	30	1008	TROPICAL DEPRESSION

# UT	C D	ate	Time	Julian	of the				
# YR	MO	DA	HHMM	Day	Day	P > 1	P > 5	P > 10	P > 30
2017	8	28	0	57993	0.00E+00	1.20E+01	2.60E-01	1.80E-01	1.14
							01	3.14E-01	1.12
							01	1.30E-01	7.17
							01	1.98E-01	9.26
							01	1.18E-01	5.97
							01	3.10E-01	2.24

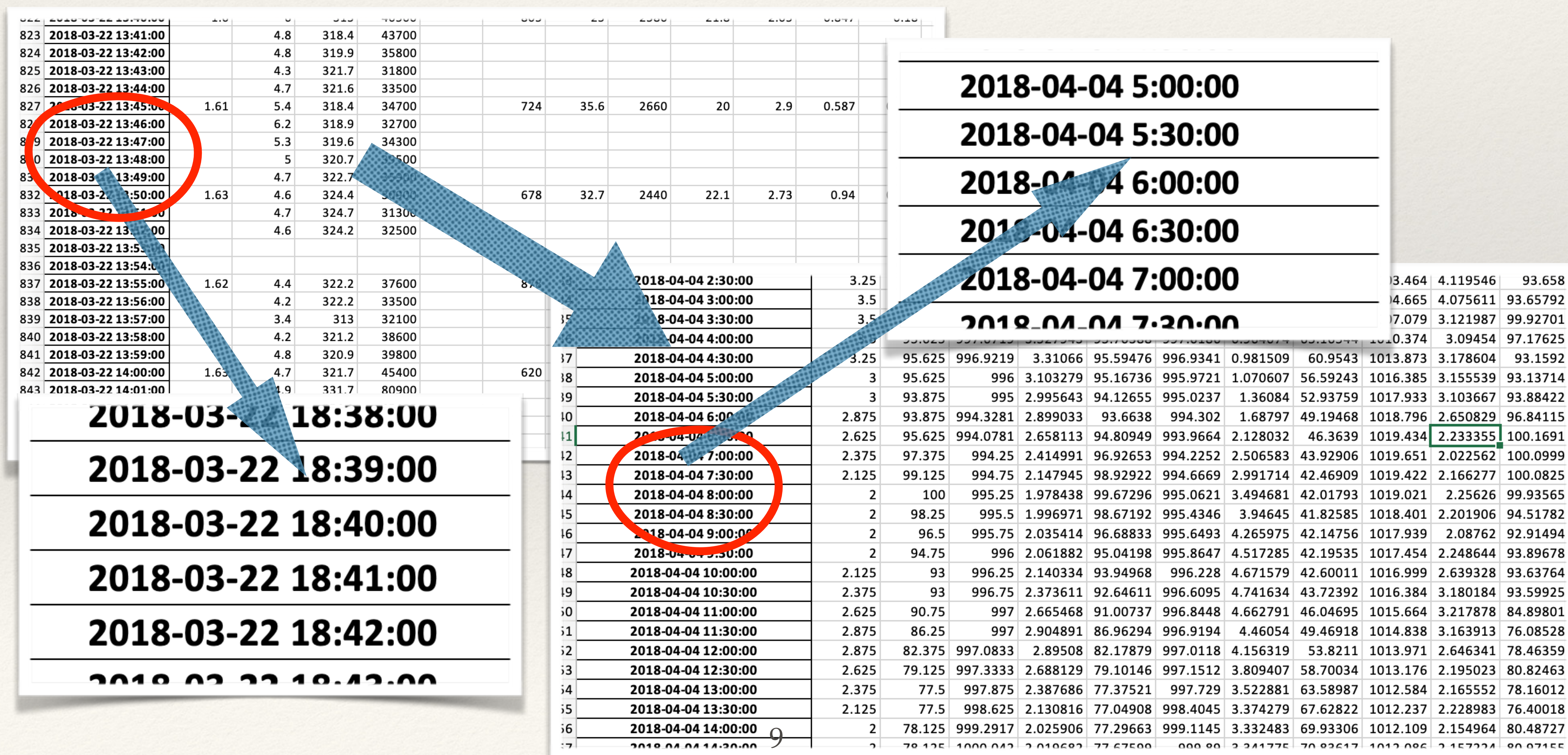
```python
def parse(x):
    y=x.split()
    z=" ".join(y[:-1])
    t=int(y[-1])
    h=t//100
    m=t%100
    z=z+" "+str(h)+" "+str(m)

    #print(x, x.split(), z, h, m, z+" "+str(h)+" "+str(m))
    return datetime.strptime(z, '%Y %m %d %H %M')

dt1=pd.read_excel('DATABASE_FOR_CALIFORNIA_GREECE_ PORTUGAL_FIRES_2018.xlsx',
'Sheet1', parse_dates = [['year', 'month', 'day', 'time']], index_col=0,
date_parser=parse)
dt1.index.name = 'date'
```

		# YR	MO	DA	HH	SPEED	DENSITY
0	0	17	8	28	0	285	3
1	1	17	8	28	1	305	3.4
2	2	17	8	28	2	309	1.7
3	3	17	8	28	3	304	2
4	4	17	8	28	4	302	2.3
5	5	17	8	28	5	304	2.4
6	6	17	8	28	6	319	3.2

	date	month	hour	density	temp	speed
2017	28	8	0			
2017	28	8	1			
2017	28	8	2			
2017	28	8	3			
2017	28	8	4			
2017	28	8	5		6.50E+04	335.27
2017	28	8	6		7.83E+04	329.43
2017	28	8	7		6.13E+04	336.79
2017	28	8	8		5.39E+04	341.07
2017	28	8	9		5.43E+04	339.36
2017	28	8	10		6.32E+04	340.8
2017	28	8	11			
2017	28	8	12			

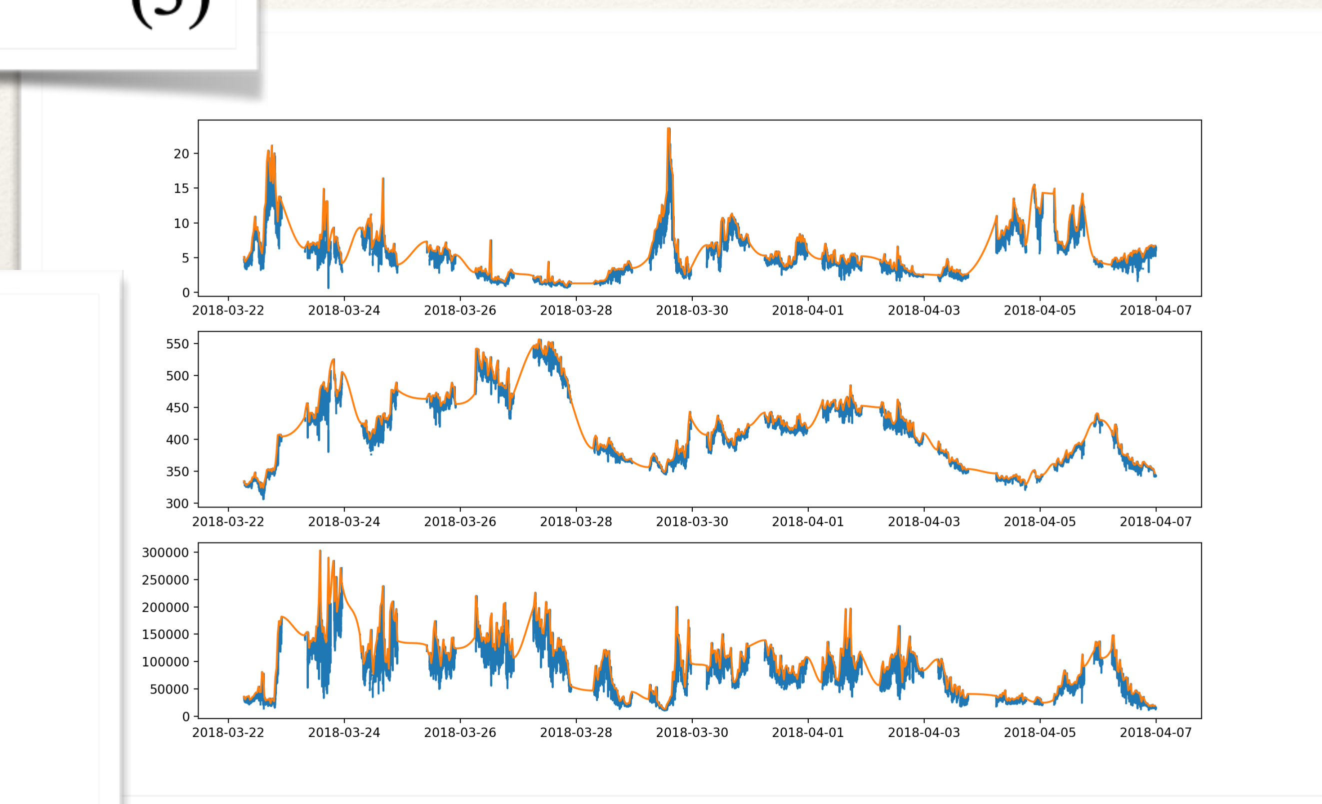
Sparse matrix

$$DF = DF_1 \cdot DF_2 \cdot DF_3 \cdot DF_4 \cdot DF_5 \qquad (2)$$



Max (mean) scale

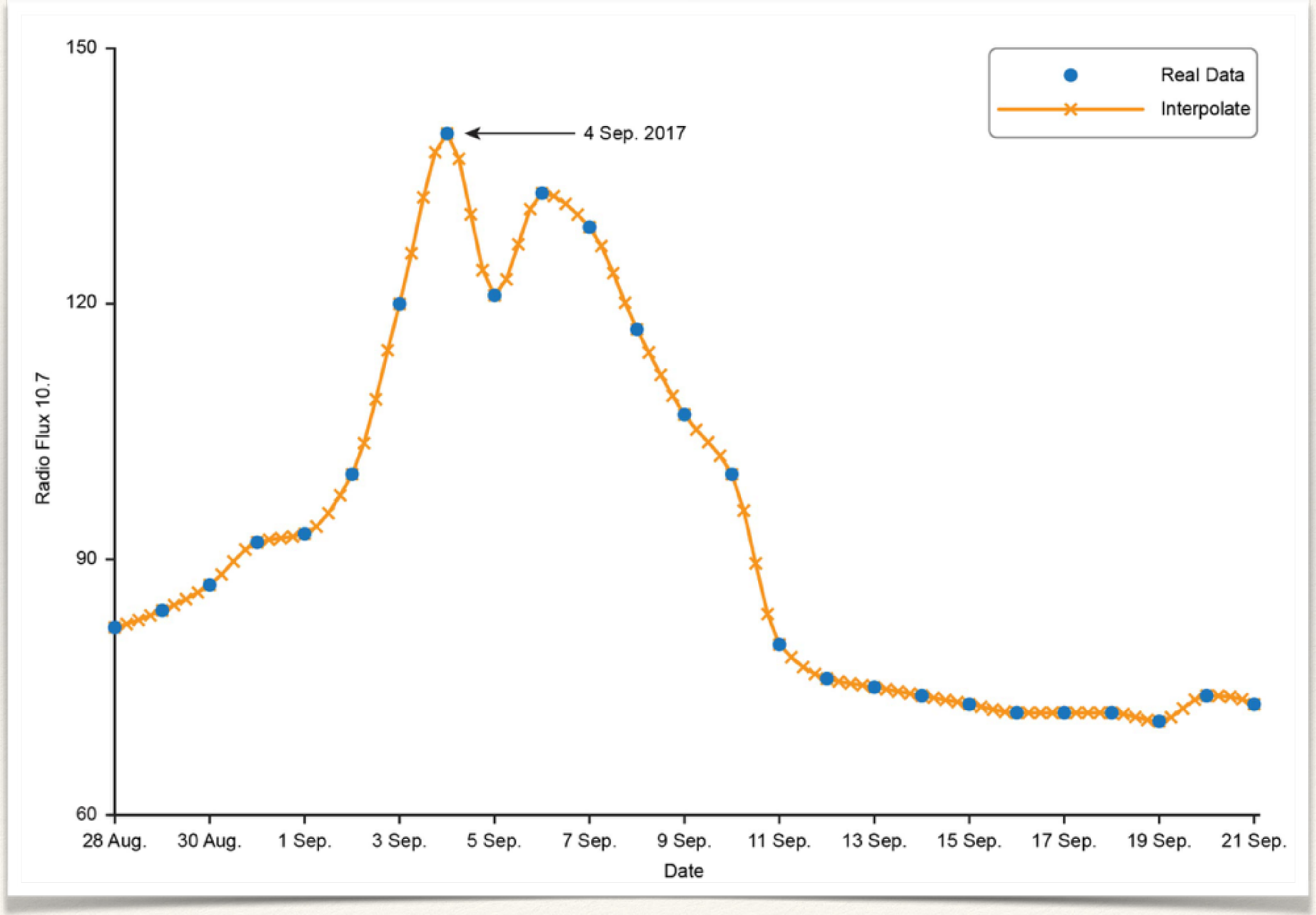
$$\overline{In}(t_i) = \sum_{j=i-b}^{i-1} In(t_j)/b, \qquad (3)$$



dt_na=DS[i-1:i+b,l],

value = numpy.mean(dt_na[~numpy.isnan(dt_na)]).

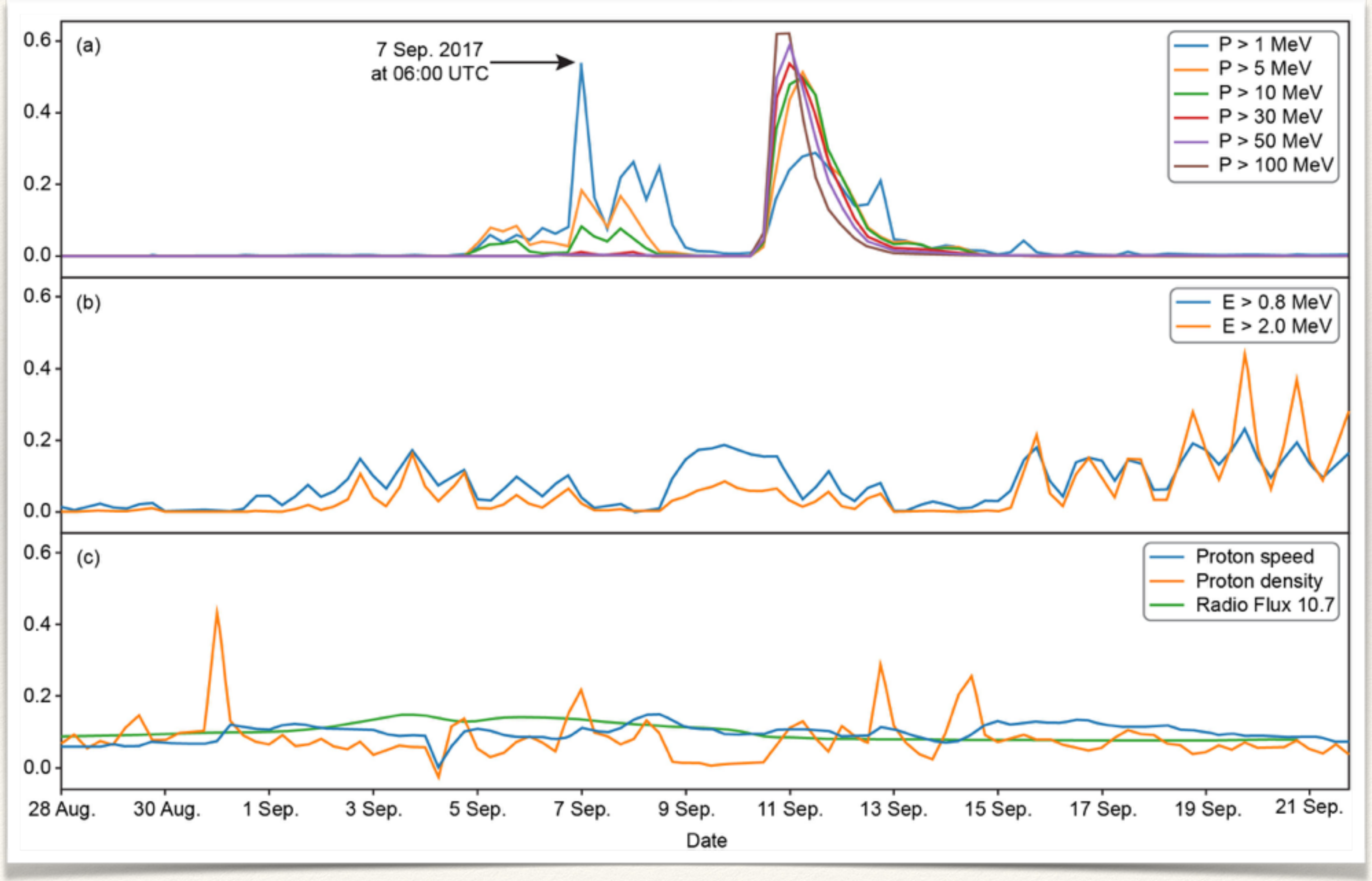
Cubic spline interpolation using Hermite polynomials (PCHIP)



Correlation analysis of input factors

	P > 1	P > 5	P > 10	P > 30	P >50	P > 100	E > 0.8	E > 2.0	Speed	Density	Radio Flux 10.7
P > 1	1.00										
P > 5	0.77	1.00									
P > 10	0.66	0.97	1.00								
P > 30	0.56	0.91	0.98	1.00							
P > 50	0.52	0.87	0.95	0.99	1.00						
P > 100	0.45	0.78	0.87	0.94	0.98	1.00					
E > 0.8	–0.19	–0.12	–0.05	0.01	0.03	0.06	1.00				
E > 2.0	–0.20	–0.17	–0.12	–0.09	–0.07	–0.06	0.81	1.00			
Speed	0.26	0.11	0.09	0.07	0.07	0.07	0.13	0.02	1.00		
Density	0.27	0.13	0.09	0.07	0.06	0.04	–0.38	–0.19	0.00	1.00	
Radio Flux 10.7	0.12	–0.04	–0.15	–0.20	–0.19	–0.16	–0.07	–0.22	–0.11	–0.10	1.00

Normalized input parameters of proton flows (a), electron flows (b), speed, density, and Radio Flux (c).



Consolidated correlation lag analysis of input factors

	P > 1	P > 5	P > 10	P > 30	P > 50	P > 100	E > 0.8	E > 2.0	Speed	Density	Radio Flux 10.7
	Wind speed of the Irma hurricane										
Max	0.21	0.37	0.33	0.20	0.20	0.18	0.73	0.54	0.39	0.07	0.86
Lag	6	6	7	7	7	9	14	13	20	7	6
	Pressure of the Irma hurricane										
Min	–0.38	–0.46	–0.43	–0.33	–0.33	–0.22	–0.81	–0.61	–0.51	0.03	–0.91
Lag	7	6	7	7	7	9	14	14	20	7	9
	Wind speed of the Jose hurricane										
Max	0.44	0.13	0.12	0.13	0.14	0.16	0.18	0.21	0.45	0.15	0.72
Lag	7	0	0	0	0	0	20	20	3	12	18
	Pressure of the Jose hurricane										
Min	–0.37	–0.02	–0.02	–0.07	–0.09	–0.11	–0.33	–0.25	–0.53	–0.24	–0.47
Lag	7	10	0	0	0	0	0	20	4	12	19
	Wind speed of the Katia hurricane										
Max	0.55	0.57	0.65	0.68	0.62	0.74	0.68	0.61	0.66	0.51	0.84
Lag	0	9	11	2	12	11	19	19	0	1	17
	Pressure of the Katia hurricane										
Min	–0.58	–0.70	–0.68	–0.76	–0.65	–0.77	–0.76	–0.68	–0.71	–0.53	–0.91
Lag	1	9	11	2	2	11	19	19	0	1	17

Parallel calculations for finding optimal models

$$T = (T_1, T_2, T_3, T_4, T_5, T_6), \quad (3)$$

$$X = (X_1, X_2, X_3, X_4, X_5), \quad (4)$$

where is time series of the wind speed and the pressure of Irma, Jose, and Katia hurricanes respectively; is time series of P > 100, E > 2.0, speed of solar wind particles, density of solar wind particles, and Radio Flux 10.7 respectively.

The task is to find for each the most accurate and adequate functional dependence of the type:

$$T_i = F_i(X, L_i, \Omega_i), \quad (5)$$

where $L_i = \{l_{ij}\}_{j=1,5}$ is the vector of optimal lags and Ω_i is parameter of the linear or the artificial neural network model

Parallel calculations for finding optimal models

$$R_i^2\left(T_i, F_i^{cv}(X, L_i, \Omega_i)\right) \xrightarrow{yields} max \quad (6)$$

Solution variables: $L_i \in Tasks, \Omega_i$

Limitations: $l_{ij} < 22;$

$$\max_{j=\overline{1,5}}\{l_{ij}\} < (lag - 2)_{Lag=\overline{0-22}},$$

where $F_i^{cv}(X, \hat{L}_i, \Omega_i)$ is the cross-validation results for k-blocks (k-fold cross-validation), Ω_i the parameter of the model, which is determined by fitting the initial model data to the target vector, the fitting method depends on the type of model (linear, neural network, etc.). The optimization was done by completely scanning all possible combinations of the lag vector L_i for each component of $X_i = \{x_{ij}\}_{j=1,5}$ from 0 to 22. The magnitude of the maximum lag was chosen from the preliminary analysis of the Table 4, where the maximum lag was 20

Parallel calculations for finding optimal models

In this case, the set of lag combinations is defined as the Cartesian product of the test lag vectors for each input parameter and is $23^5 \cdot 11 \cdot 6$ = 424,798,638

$$Tasks(22) = \prod_{j=1,5} L(22), \tag{7}$$

where $L(22) = \{0,1,\ldots,22\}$.

The implementation of the Cartesian product by means of Python was carried out as follows

```
lag_list=[list(range(lag+1))]*len(X),
task_lag=list(itertools.product(*lag_list)),
```

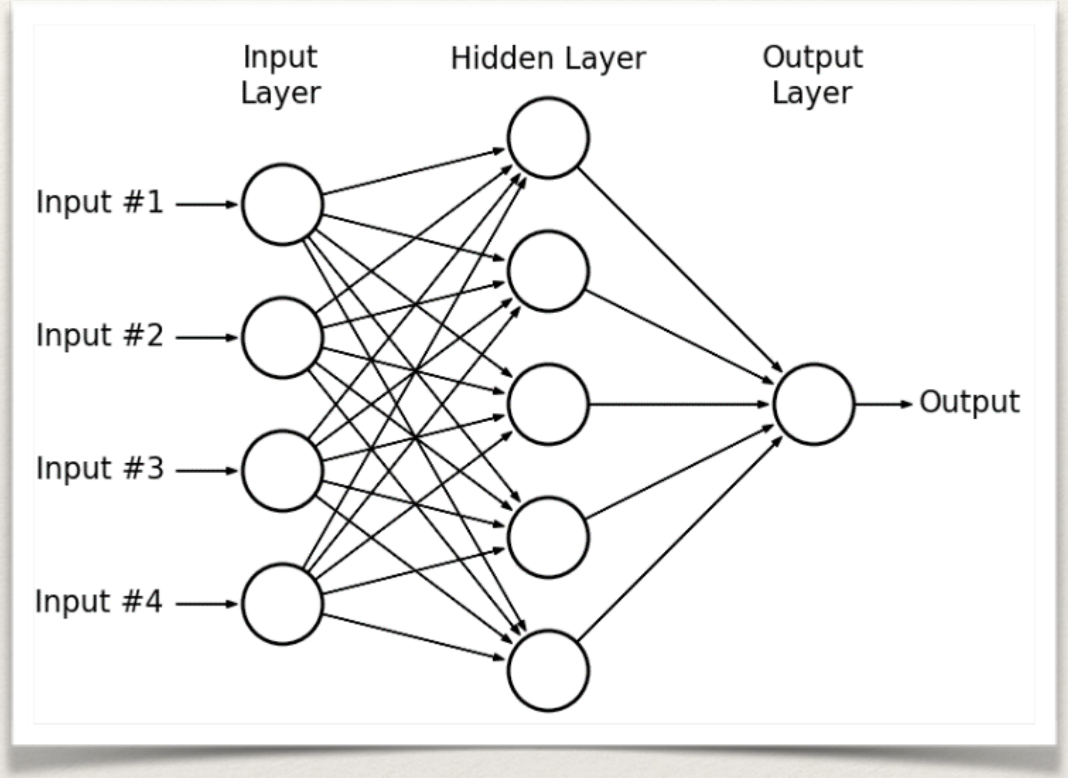
Parallel calculations algorithm for finding an optimal model

1. The first maximum number of lags is determined *lag = 0*.
2. A set of tasks is formed based on the equation (7):
3. For the first run *Tasks (lag)*.
4. For the next runs in order to avoid repetitions of tasks the difference of sets needs to be calculated *Tasks (lag) '= Tasks (lag) \ Tasks (lag-1)*.
5. The optimal model is found according to equation (6).
6. If the maximum lag value for any component of the optimal model does not exceed *lag-2*, it is assumed that the optimal value is found and the algorithm is completed.
7. If *lag = 22*, the algorithm is completed and is considered to have no optimal value.
8. Increase *lag + = 1* and move to step 1.

Multilayer perceptrons

ANN:
Type: Multilayer perceptrons (MLPs) with back propagation
Inputs: 5
Output:1
Hidden layer: 1
Number of neurons: 7
Method of training: quasi-Newtonian
Activation function: logistic function

Python:
framework: sklearn.neural_network
function: MLPRegressor
fitting: fit and cross_val_predict



Ensemble of models by Delphi method

1. Several neural networks were created and studied for each model according to equation (5). In our case, their optimal number was nine. Their increase did not improve the result.
2. Predictive values were calculated on the test sets of data using the cross-validation method for each of the networks. The result was a matrix of type:

$$Res_i = \begin{bmatrix} f_{i1}^1 & \cdots & f_{im}^1 \\ \vdots & \ddots & \vdots \\ f_{i1}^9 & \cdots & f_{im}^9 \end{bmatrix}, \qquad (6)$$

where *m* is the size of the training sample for a particular vector of the goals, the upper index is the serial number of the neural network.

3. Each column was sorted and then 10% of records with minimum and maximum values were removed from the records.
4. For the remaining values for each of the columns the median was determined, which was considered to be the result.

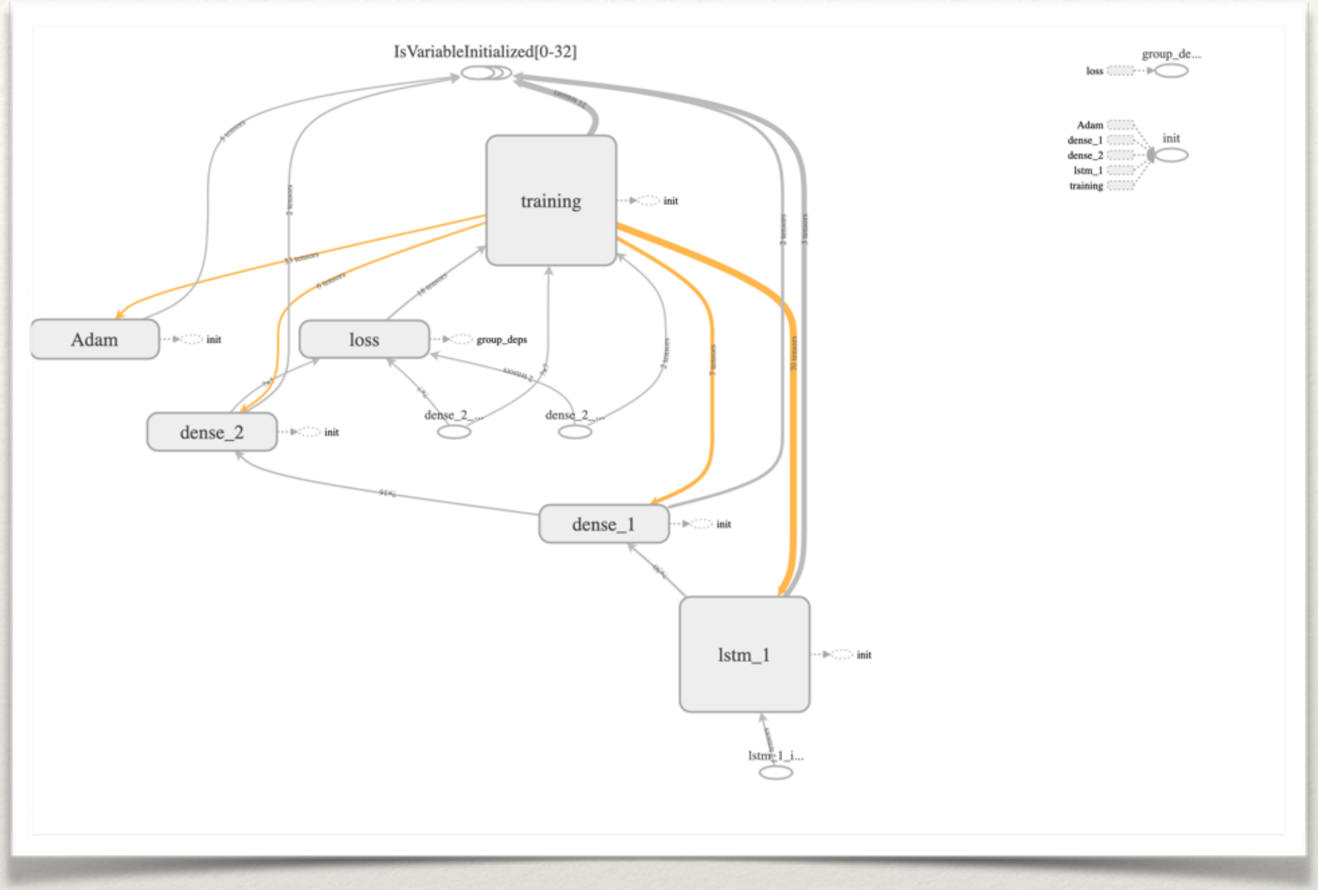
*Res =numpy.sort(Res, axis=0)[int(len(Res)*0.1):- int(len(Res)*0.1), :],*

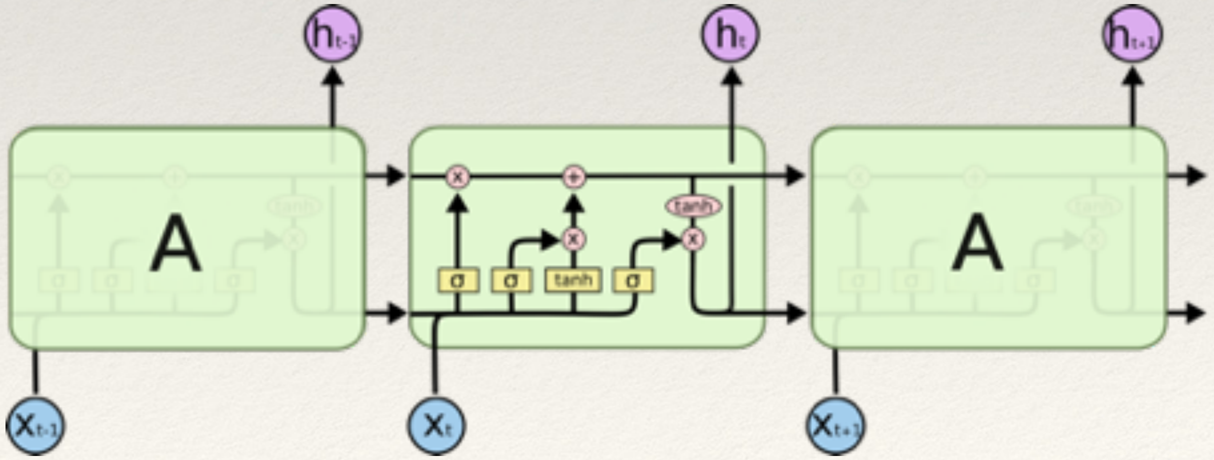
Recurrent neural network with long short-term memory (LSTM)

LSTM:

Inputs: 6
Output:1
Hidden layer: 1 LSTM
Number of neurons: 7
Method of training: adam
Loss function: mse

Python:
framework: TensorFlow
fitting: fit and cross_val_predict



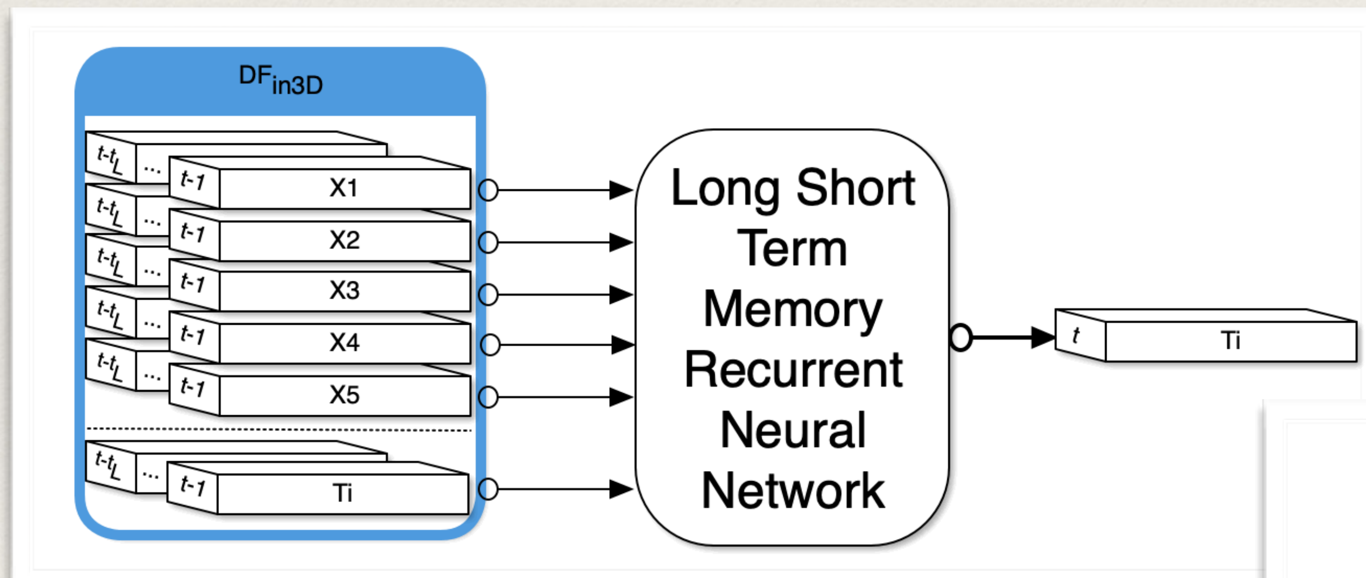


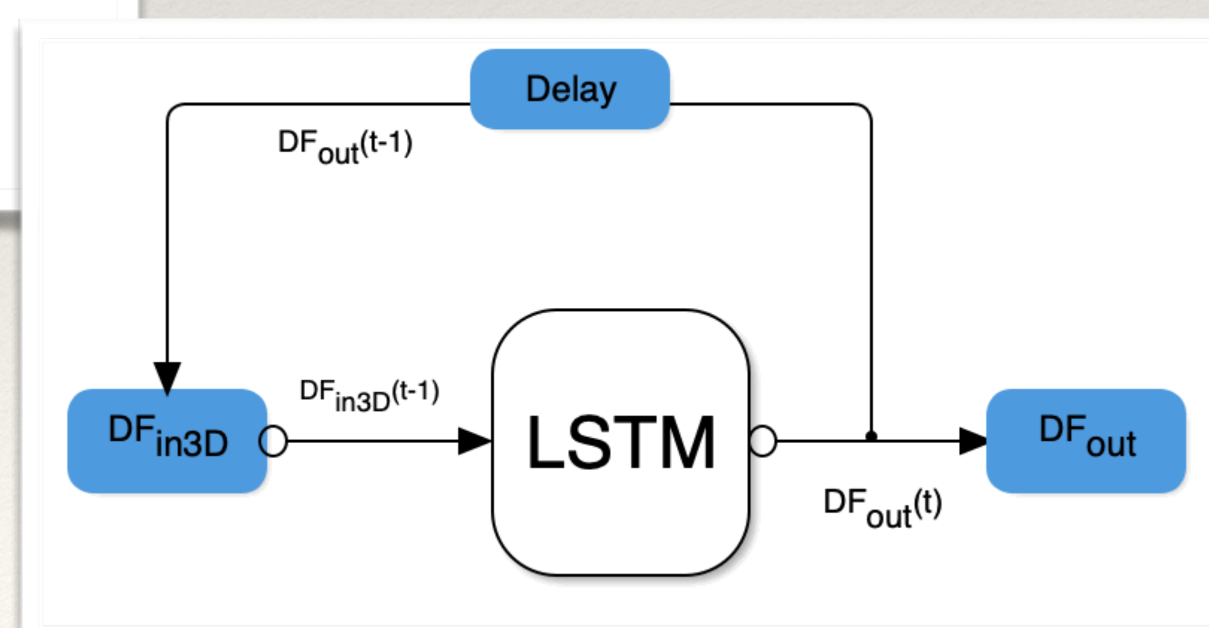
Recurrent neural network with long short-term memory (LSTM)

$$X_L^i = (X_1(t-1), \dots, X_5(t-1), T_i(t-1), X_1(t-t_L), \dots, X_5(t-t_L), T_i(t-t_L) >) \quad (7)$$

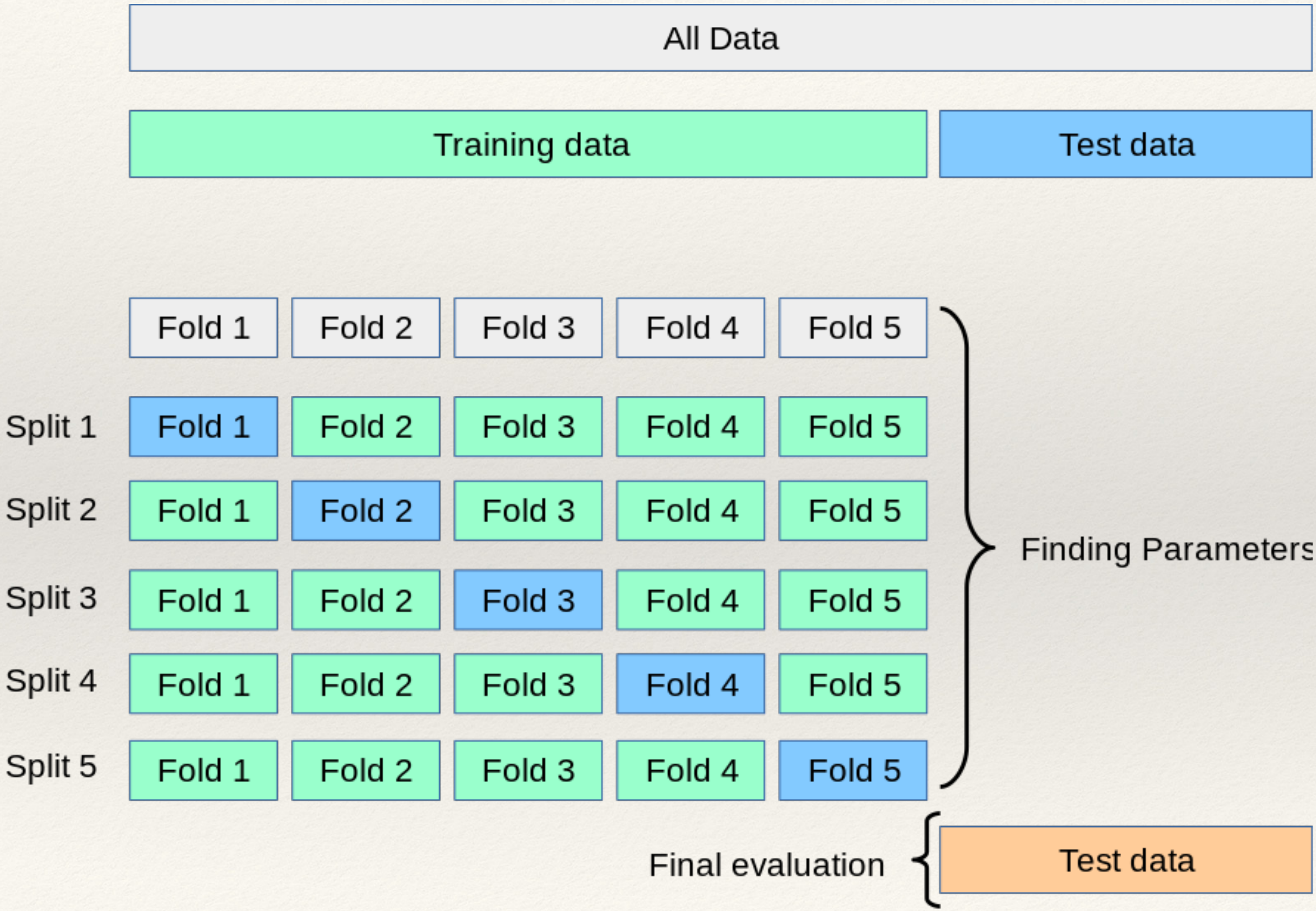
$$X_{3D,L}^i = \left(x_1(t-l)_{l=\overline{1,L}}, \dots, x_5(t-l)_{l=\overline{1,L}}, T_i(t-l)_{l=\overline{1,L}}\right) \quad (8)$$

where t – row index, L– maximum lag value, i – target index (2)

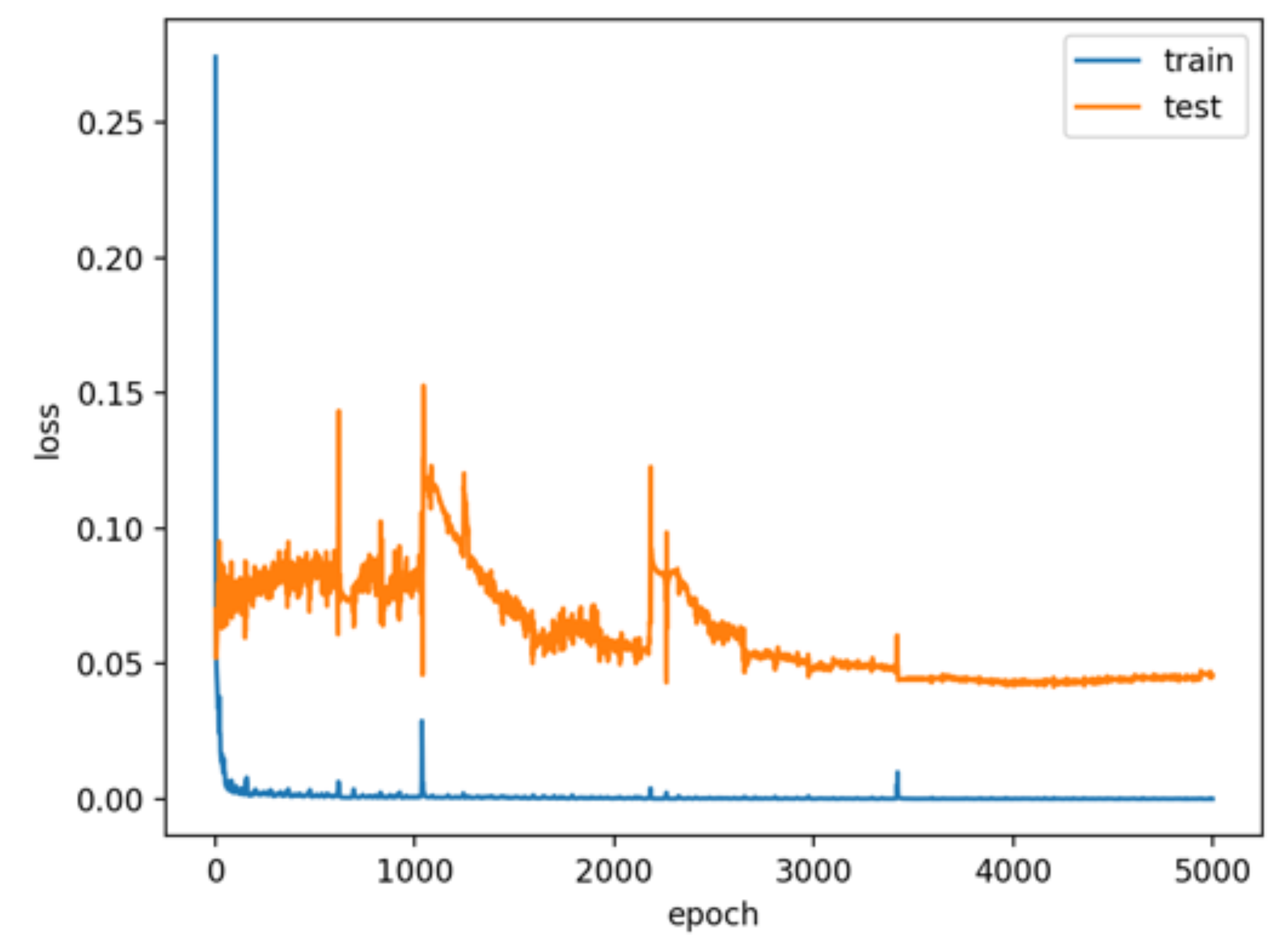




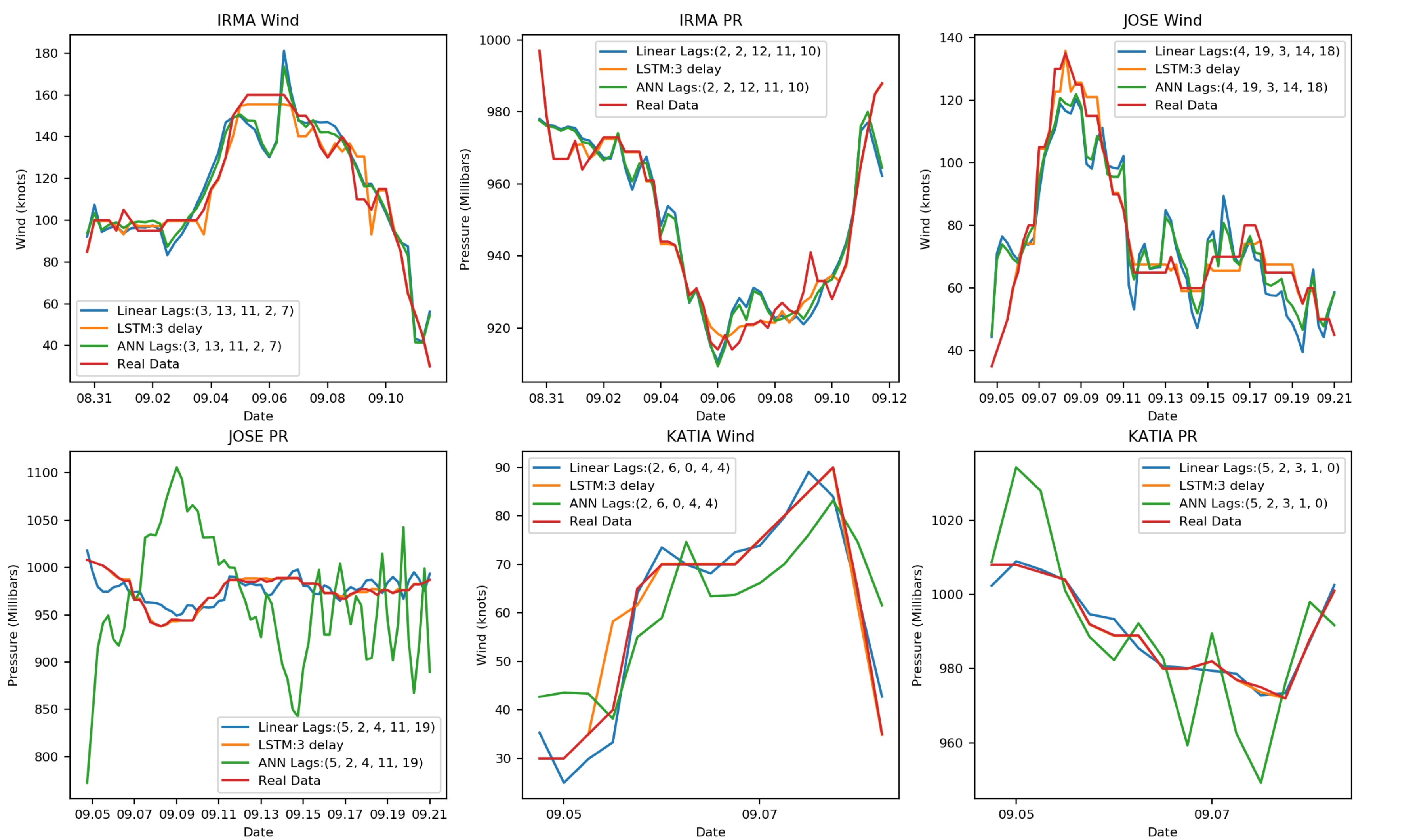
Cross-validation



Overfitting test. Dynamics of the mean square error during the fitting LSTM for the training and test samples



Parallel calculations results of artificial neural networks and linear models



Results of hurricane forecasting with linear models and artificial neural networks for: (a) Wind speed of the Irma hurricane, (b) Pressure of the Irma hurricane, (c) Wind speed of the Jose hurricane, (d) Pressure of the Jose hurricane, (e) Wind speed of the Katia hurricane, (f) Pressure of the Katia hurricane

Accuracy analysis

Hurricane	Parameter	Model: Equation	Model: Type	Numbers of tests models	Lags	R^2 Full dataset	R^2 Cross validation
Irma	Wind speed	$F_1(X, L_1, \Omega_1^{Lin})$	Linear	1,048,576	L_1 =(3, 13, 11, 2, 7)	0.89	0.85
		$\{F_1(X, L_1, \Omega_1^{ANN})\}$	ANN	99		0.89	0.75
		$\{F_1(X_{3D,L}, L_{LSTM}, \Omega_1^{LSTM})\}$	LSTM	99	$L_{LSTM} = \{l_i = \overline{1,4}\}_{i=\overline{1,6}}$	0.98	0.88
	Pressure	$F_2(X, L_2, \Omega_2^{Lin})$	Linear	759,375	L_2 = (2, 2, 12, 11, 10)	0.90	0.88
		$\{F_2(X, L_2, \Omega_2^{ANN})\}$	ANN	99		0.90	0.87
		$\{F_2(X_{3D,L}, L_{LSTM}, \Omega_1^{LSTM})\}$	LSTM	99	$L_{LSTM} = \{l_i = \overline{1,4}\}_{i=\overline{1,6}}$	0.99	0.93
Jose	Wind speed	$F_3(X, L_4, \Omega_4^{Lin})$	Linear	5,153,632	L_3 = (4, 19, 3, 14, 18)	0.86	0.77
		$\{F_3(X, L_4, \Omega_4^{ANN})\}$	ANN	99		0.86	0.74
		$\{F_3(X_{3D,L}, L_{LSTM}, \Omega_1^{LSTM})\}$	LSTM	99	$L_{LSTM} = \{l_i = \overline{1,4}\}_{i=\overline{1,6}}$	0.98	0.61
	Pressure	$F_4(X, L_4, \Omega_4^{Lin})$	Linear	5,153,632	L_4 = (5, 2, 4, 11, 19)	0.69	0.56
		$\{F_4(X, L_4, \Omega_4^{ANN})\}$	ANN	99		0.58	0.70
		$\{F_4(X_{3D,L}, L_{LSTM}, \Omega_1^{LSTM})\}$	LSTM	99	$L_{LSTM} = \{l_i = \overline{1,4}\}_{i=\overline{1,6}}$	0.98	0.45
Katia	Wind speed	$F_5(X, L_5, \Omega_5^{Lin})$	Linear	100,000	L_5 = (2, 6, 0, 4, 4)	0.98	0.96
		$\{F_5(X, L_5, \Omega_5^{ANN})\}$	ANN	99		0.72	0.34
		$\{F_5(X_{3D,L}, L_{LSTM}, \Omega_1^{LSTM})\}$	LSTM	99	$L_{LSTM} = \{l_i = \overline{1,4}\}_{i=\overline{1,6}}$	0.95	0.48
	Pressure	$F_6(X, L_6, \Omega_6^{Lin})$	Linear	59,049	L_6 = (5, 2, 3, 1, 0)	0.98	0.96
		$\{F_6(X, L_6, \Omega_6^{ANN})\}$	ANN	99		0.65	0.53
		$\{F_5(X_{3D,L}, L_{LSTM}, \Omega_1^{LSTM})\}$	LSTM	99	$L_{LSTM} = \{l_i = \overline{1,4}\}_{i=\overline{1,6}}$	0.99	0.38
Total			Linear	12,274,264			
			ANN	594			
			LSTM	594			

Linear models

$F_1(X, L_1, \Omega_1^{Lin}) = -16.44 - 1.09 \cdot x(3)_1 + 2.88 \cdot 10^{-04} \cdot x(13)_2 - 0.05 \cdot x(11)_3 + 0.85 \cdot x(2)_4 + 1.40 \cdot x(7)_5,$

$F_2(X, L_2, \Omega_2^{Lin}) = 1067.52 + 0.55 \cdot x(2)_1 - 5.42 \cdot 10^{-04} \cdot x(2)_2 + 0.02 \cdot x(12)_3 + 0.63 \cdot x(11)_4 - 1.17 \cdot x(10)_5,$

$F_3(X, L_3, \Omega_3^{Lin}) = -80.15 - 0.71 \cdot x(4)_1 + 4.93 \cdot 10^{-04} \cdot x(19)_2 + 0.12 \cdot x(3)_3 + 1.62 \cdot x(14)_4 + 0.84 \cdot x(18)_5,$

$F_4(X, L_2, \Omega_2^{Lin}) = 1073.42 + 0.54 \cdot x(5)_1 - 2.83 \cdot 10^{-04} \cdot x(2)_2 - 0.08 \cdot x(4)_3 - 1.27 \cdot x(11)_4 - 0.52 \cdot x(19)_5,$

$F_5(X, L_5, \Omega_5^{Lin}) = -413.61 - 94.62 \cdot x(2)_1 - 8.08 \cdot 10^{-04} \cdot x(6)_2 + 0.17 \cdot x(0)_3 - 1.88 \cdot x(4)_4 + 3.14 \cdot x(4)_5,$

$F_6(X, L_6, \Omega_6^{Lin}) = 783.42 - 26.24 \cdot x(5)_1 + 1.42 \cdot 10^{-04} \cdot x(2)_2 + 0.12 \cdot x(3)_3 - 2.30 \cdot x(1)_4 + 1.19 \cdot x(0)_5.$

Sensitivity analysis

$$V = \begin{bmatrix} 0.1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0.1 \end{bmatrix}_{5\times 5}$$

$$A^r = \begin{bmatrix} x_1^r & \cdots & x_5^r \\ \vdots & \ddots & \vdots \\ x_1^r & \cdots & x_5^r \end{bmatrix}.$$

$$T^r = (V+1)\cdot A^r = \begin{bmatrix} 1.1\cdot x_1^r & \cdots & 1.0\cdot x_5^r \\ \vdots & \ddots & \vdots \\ 1.0\cdot x_1^r & \cdots & 1.1\cdot x_5^r \end{bmatrix}$$

$$S_i^r = F_i\left(T^r, L_i, \Omega_i^{Lin(ANN)}\right) = \begin{bmatrix} f_{i,x_1}^r \\ \vdots \\ f_{i,x_5}^r \end{bmatrix}.$$

$$S_i = \begin{bmatrix} (S_i^1)^T \\ \vdots \\ (S_i^N)^T \end{bmatrix}.$$

$$M_i = \{m_i^r\}_{r=\overline{1-N}} = F_i\left(X, L_i, \Omega_i^{Lin(ANN)}\right)$$

$$Mx_i = \begin{bmatrix} m_i^1 & \cdots & m_i^1 \\ \vdots & \ddots & \vdots \\ m_i^N & \cdots & m_i^N \end{bmatrix}_{N\times 5}$$

$$D = (S_i - Mx_i)/Mx_i,$$

$$Sens = \overline{D}_{col}.$$

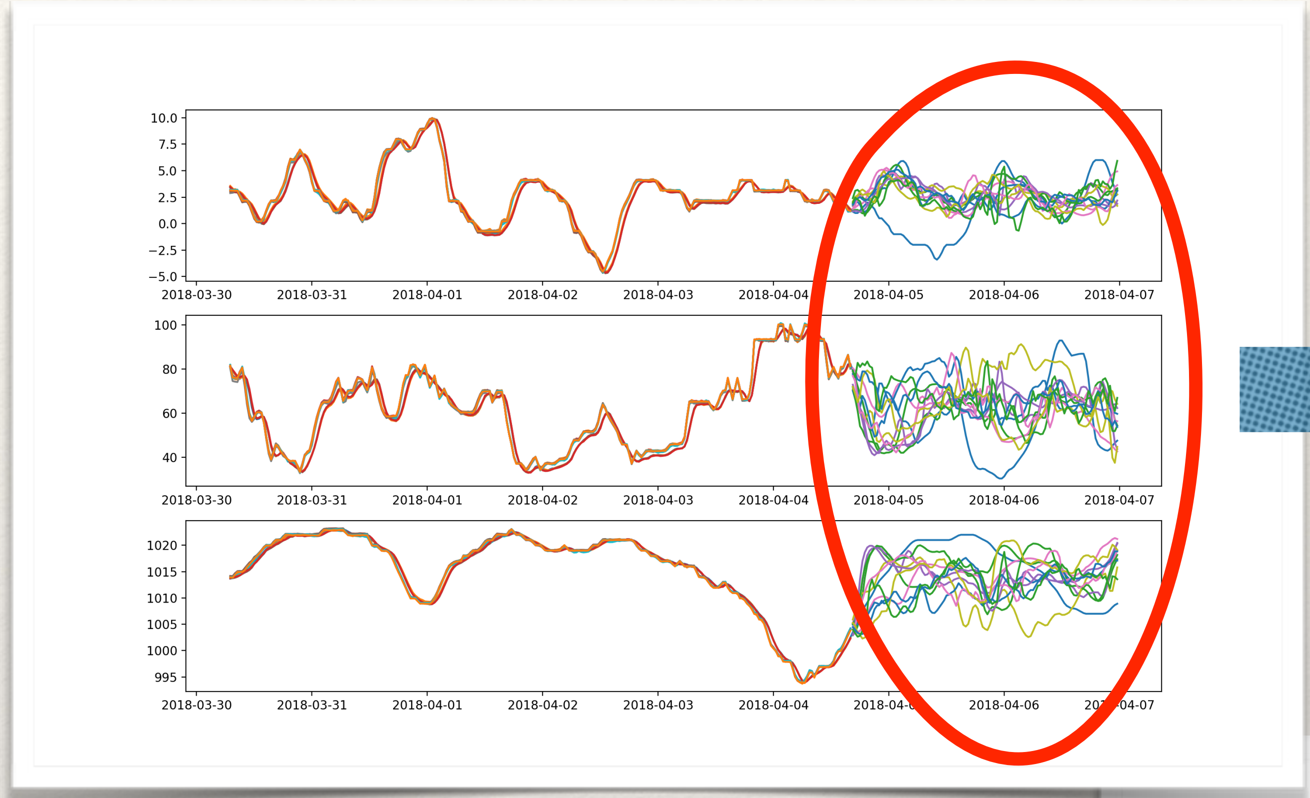
Sensitivity analysis

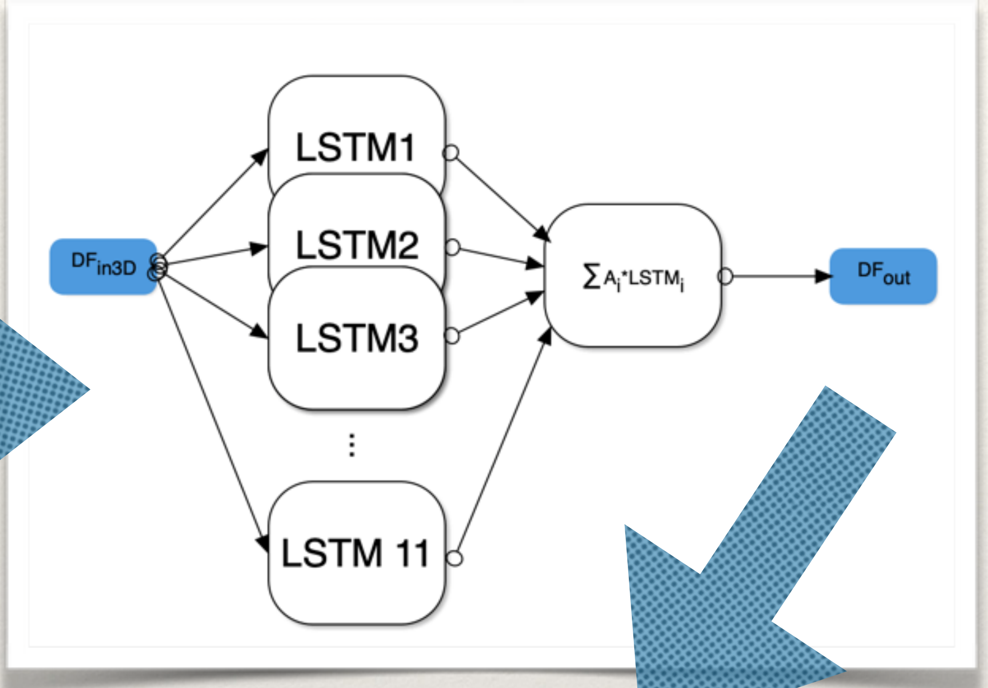
Hurricane	Parameter	Model	P > 100	E > 2.0	Speed	Density	Radio Flux 10.7
Irma	Wind speed	Linear	–0.63%	0%	–2.51%	0%	14%
		ANN	–0.65%	0%	–2.64%	0%	13%
		LSTM	-13%	-9%	-28%	40%	0%
	Pressure	Linear	0%	–0.04%	0%	0%	–1.36%
		ANN	0%	–0.04%	0%	0%	–1.36%
		LSTM	0%	-1%	-2%	-1%	0%
Jose	Wind speed	Linear	–0.26%	1%	9%	1%	11%
		ANN	–0.26%	1%	9%	1%	11%
		LSTM	-0%	-18%	2%	-4%	124%
	Pressure	Linear	0%	–0.04%	–0.42%	–0.04%	–0.53%
		ANN	0%	1%	4%	0%	5%
		LSTM	-0%	-0%	-7%	4%	-45%
Katia	Wind speed	Linear	–1.07%	–1.19%	18%	–1.17%	75%
		ANN	0%	–1.30%	9%	–0.64%	3%
		LSTM	5%	25%	548%	207%	1%
	Pressure	Linear	–0.02%	0%	1%	–0.07%	1%
		ANN	0%	–0.14%	3%	1%	7%
		LSTM	-3%	1%	7%	-10%	-8%

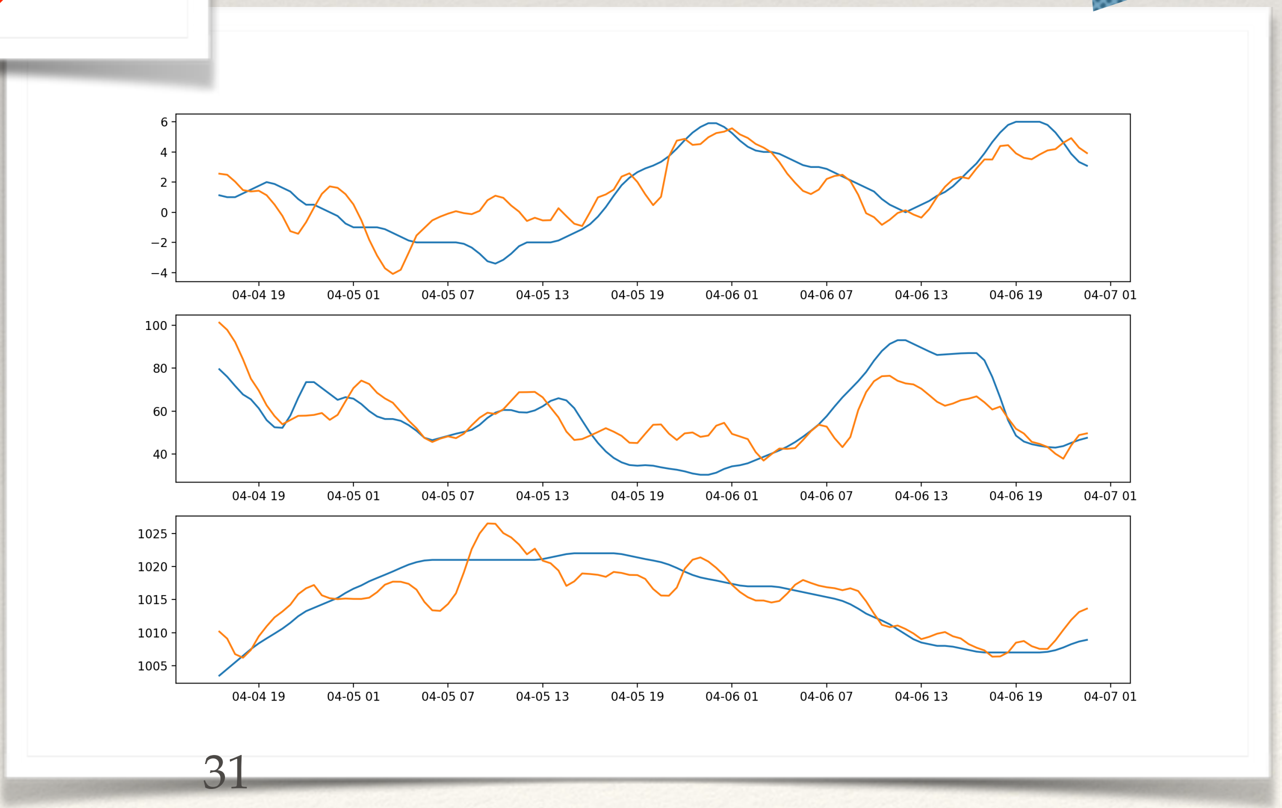
Sensitivity analysis

Hurricane	Parameter	Model	P > 100	E > 2.0	Speed	Density	Radio Flux 10.7
Irma	Wind speed	Linear	–0.63%	0%	–2.51%	0%	14%
		ANN	–0.65%	0%	–2.64%	0%	13%
		LSTM	-13%	-9%	-28%	40%	0%
	Pressure	Linear	0%	–0.04%	0%	0%	–1.36%
		ANN	0%	–0.04%	0%	0%	–1.36%
		LSTM	0%	-1%	-2%	-1%	0%
Jose	Wind speed	Linear	–0.26%	1%	9%	1%	11%
		ANN	–0.26%	1%	9%	1%	11%
		LSTM	-0%	-18%	2%	-4%	124%
	Pressure	Linear	0%	–0.04%	–0.42%	–0.04%	–0.53%
		ANN	0%	1%	4%	0%	5%
		LSTM	-0%	-0%	-7%	4%	-45%
Katia	Wind speed	Linear	–1.07%	–1.19%	18%	–1.17%	75%
		ANN	0%	–1.30%	9%	–0.64%	3%
		LSTM	5%	25%	548%	207%	1%
	Pressure	Linear	–0.02%	0%	1%	–0.07%	1%
		ANN	0%	–0.14%	3%	1%	7%
		LSTM	-3%	1%	7%	-10%	-8%

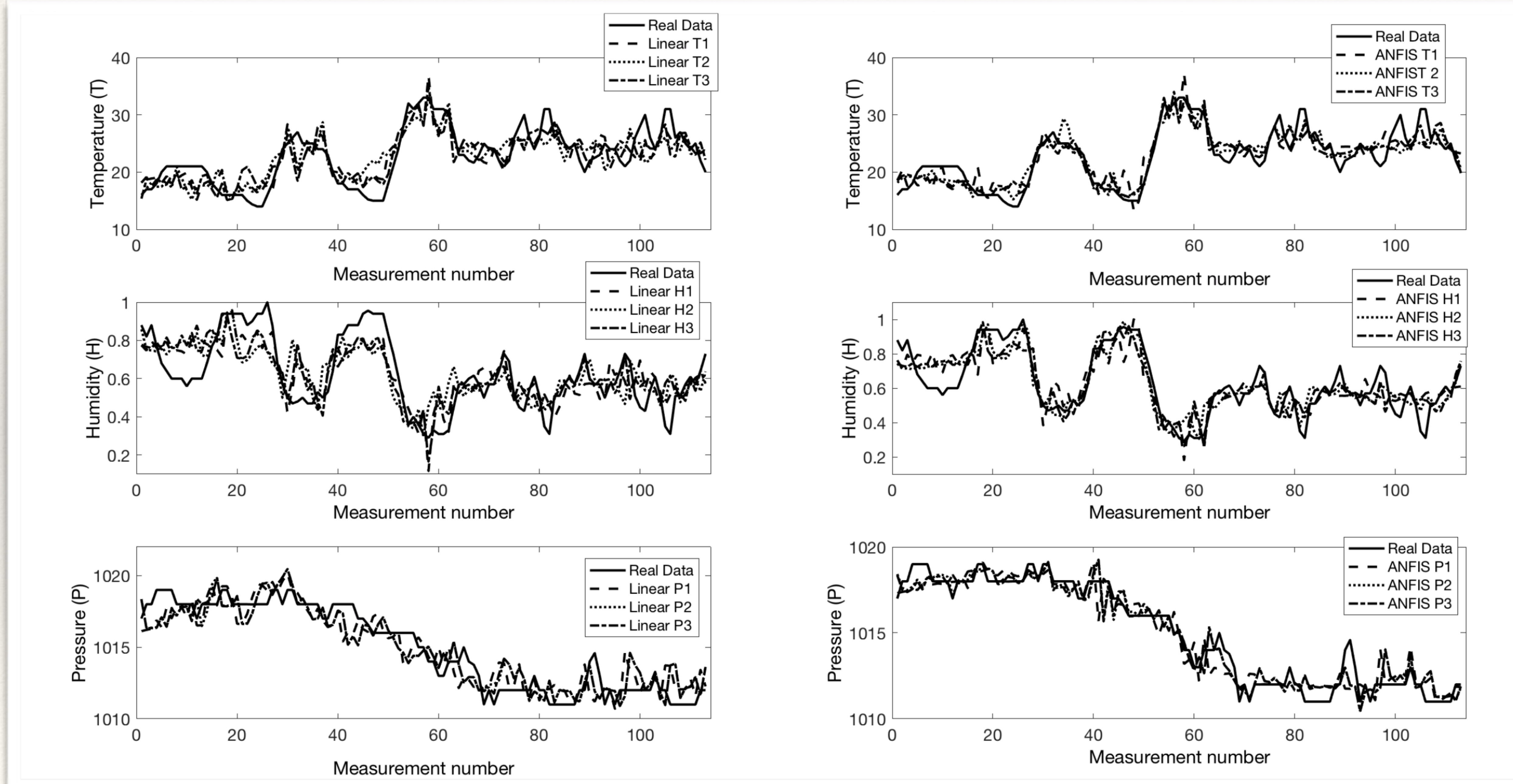
Detroit (USA) weather forecasting by LSTM ensemble



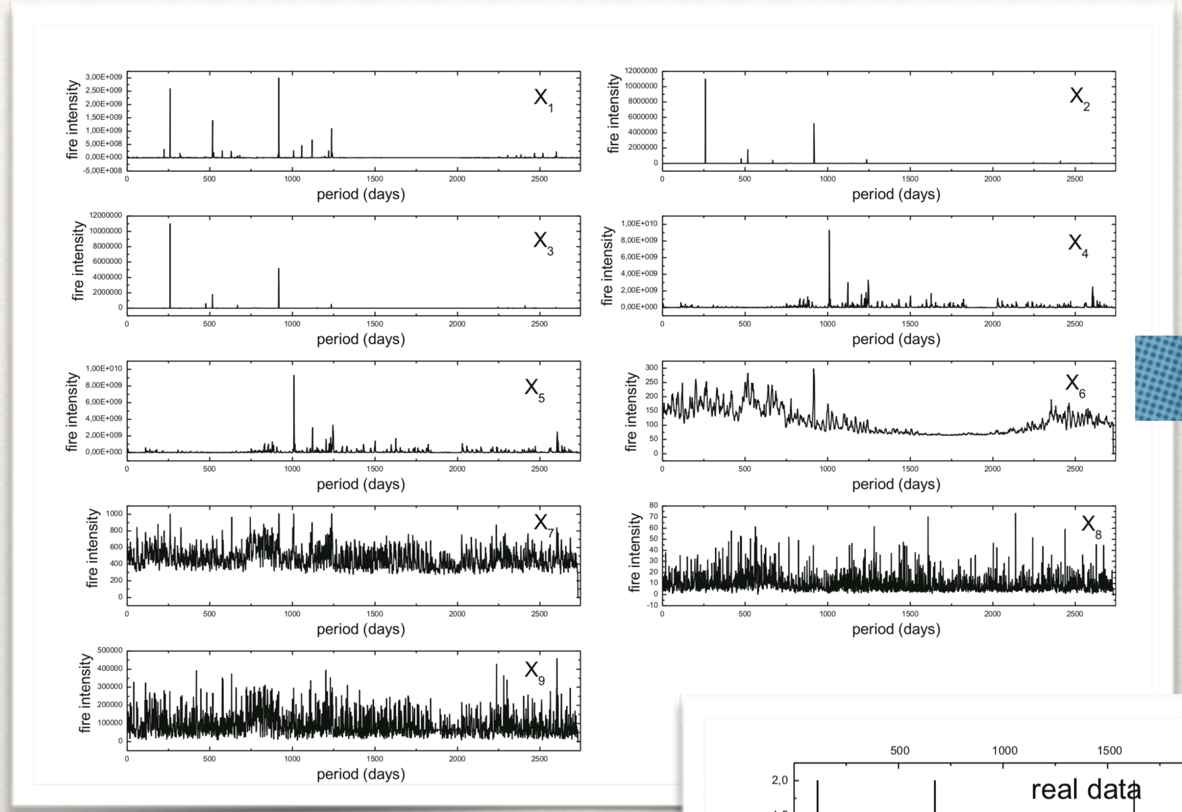


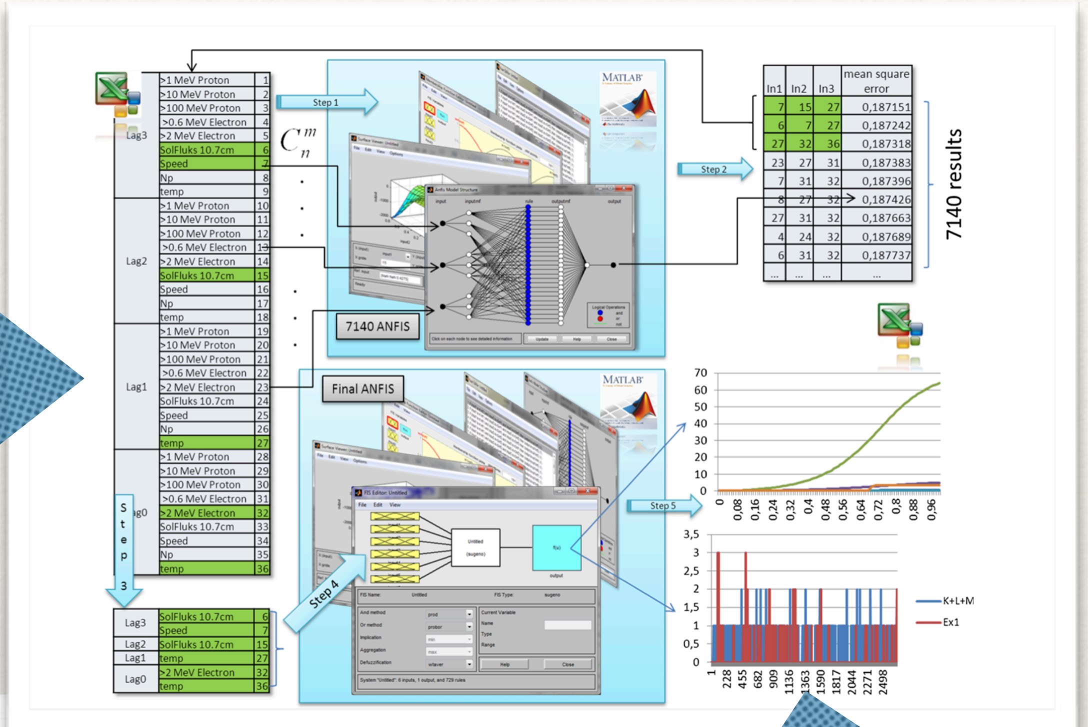


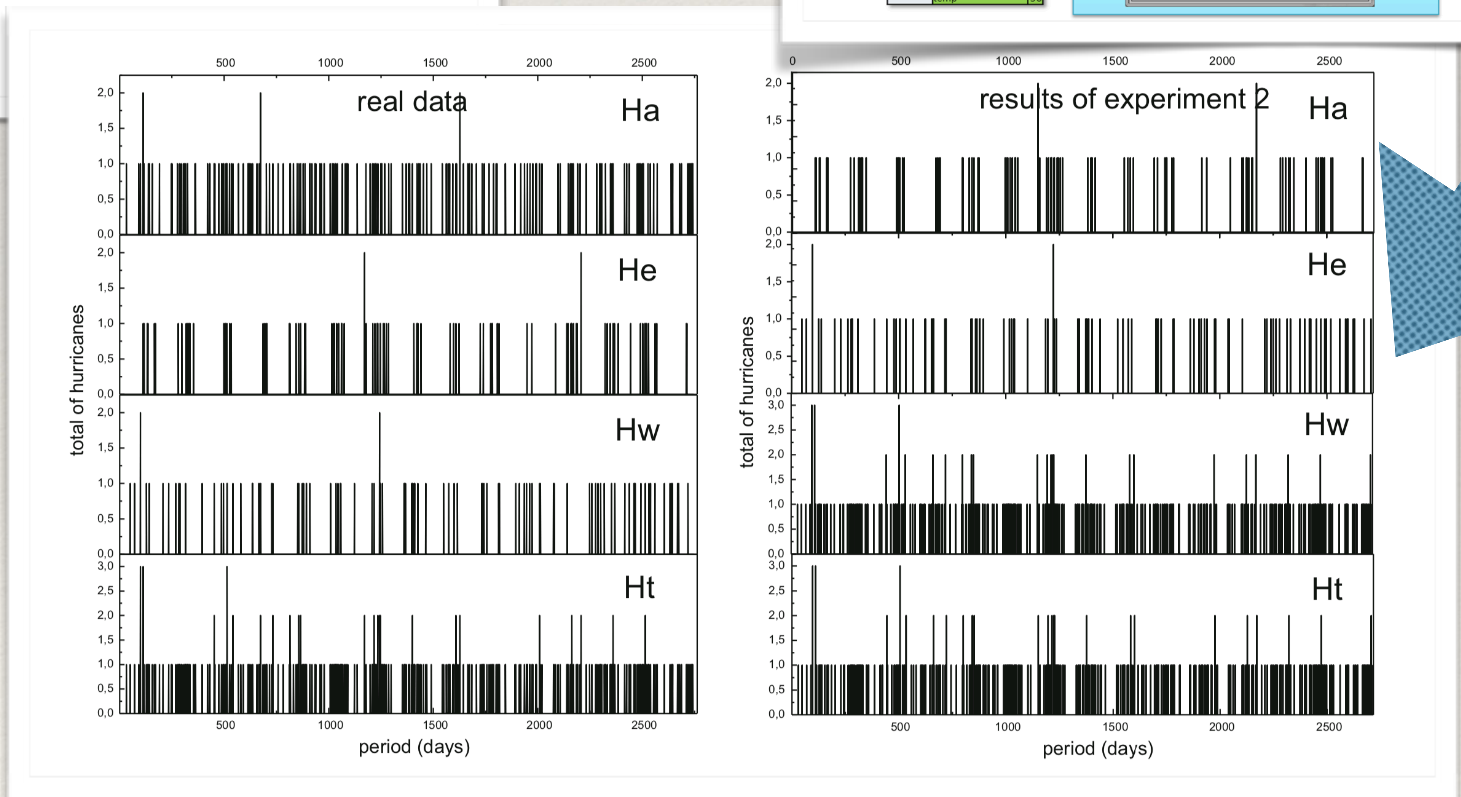
Linear vs ANFIS. Portugal



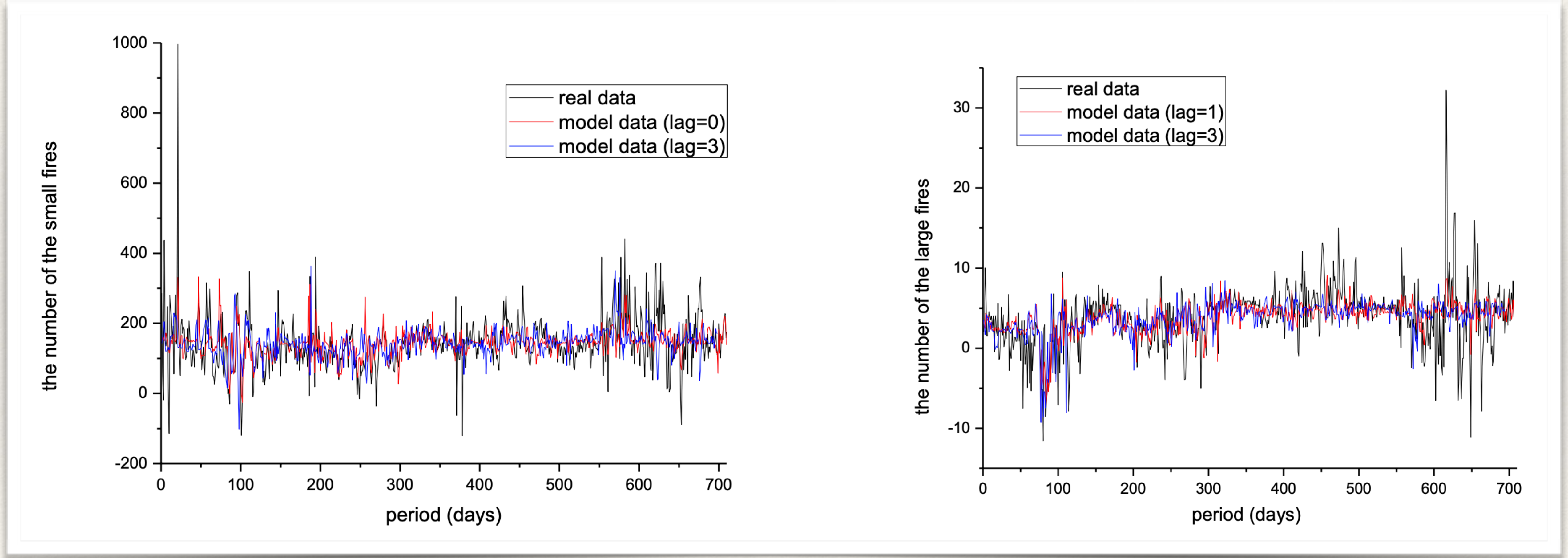
Hurricanes forecasting by ANFIS



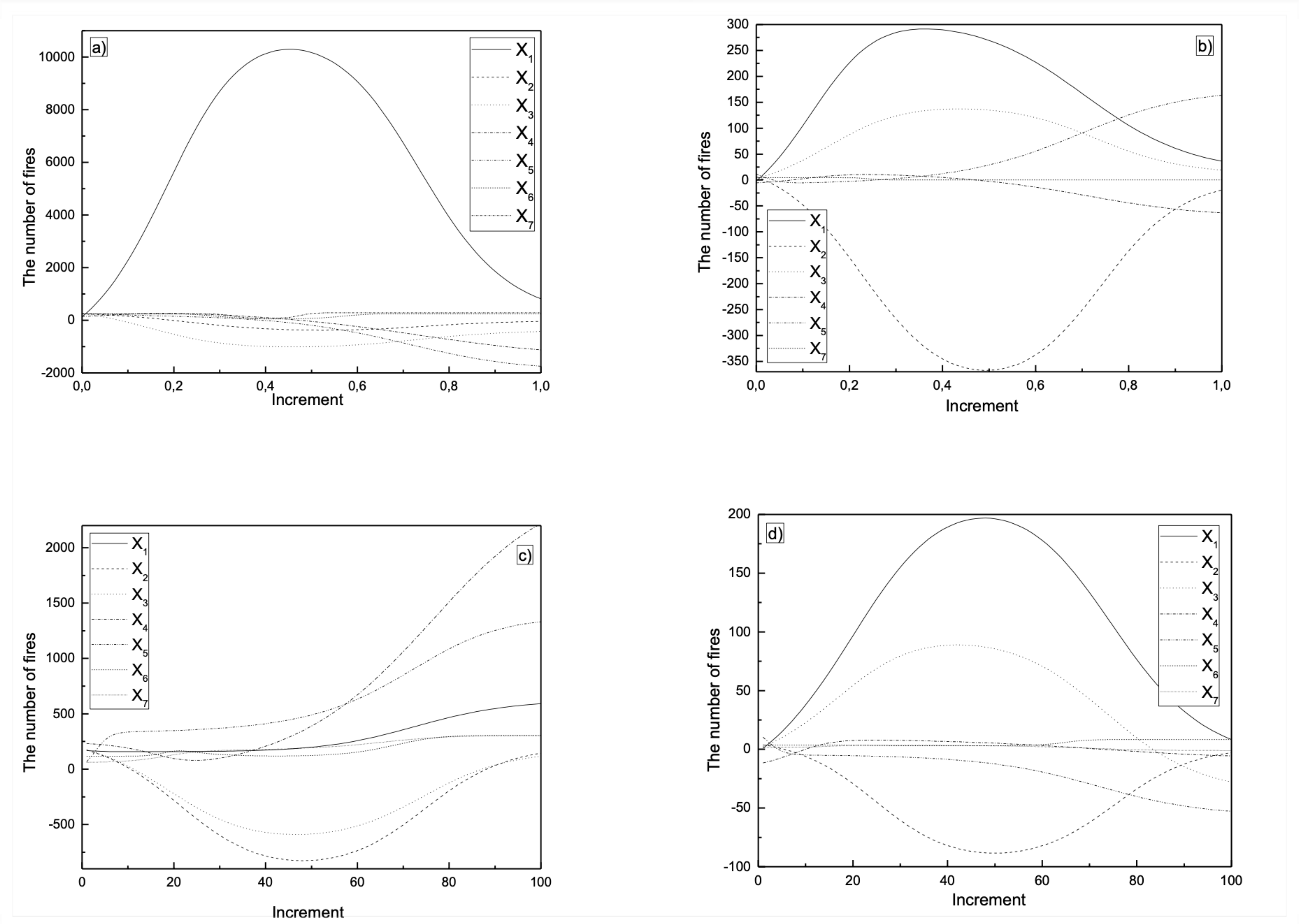




Forest fires forecasting for USA



Sensitivity of factors



Conclusions

Considering the potential prognostic models, one should certainly bear in mind that for solar flares from active regions located at the East of the helilongitude, the time delay (between emission and the ground level enhancement onset) can be from several hours up to days. Almost all diffusion models involving solar particle transport in the interplanetary medium show that the maximum time delay is proportional to the square of the distance traveled.

The efficiency of the penetration depends on the degree to which the interplanetary magnetic field provides input of the particle flux to the region with the given angle and/or in what percent relation the particles of the given direction are present in the flux with a high angular isotropy.

Research in this paper has shown that applied model is accurate and adequate to predict the appearance of hurricanes 2–4 days ahead, after the outbreak of SW. High correlation coefficients sustain the previous conclusion. About 90% of variations of the Irma hurricane can be explained by the model. Jose is the hurricane in the Pacific Ocean, which has larger scale, and therefore the processes of the influence of external factors are more inertial, which explains a bigger lag in the calculations. The sensitivity analysis revealed that Radio Flux 10.7 has the greatest impact on wind speed of the hurricanes, except in the case of the Katia hurricane. In the general picture of the change in pressure and wind speed over a longer period, there are other factors that were not taken into account in the model. Therefore, the model for Jose was less accurate, but quite adequate. The Katia hurricane was the least lengthy and the data were not enough to test the hypothesis in this case. In all cases LSTM models showed the best results. But for effective use it the big data sets should be obtained.

The coupling of the stratosphere with surface climate is one good candidate to better understand the signals of the future climate changes. Vertical wind shear was shown to be a much more fundamental component for major hurricane development and maintenance

Thank you for attention

Prof. Yaroslav Vyklyuk Dr.Sc.