Forecasting COVID-19 pandemic using an echo state neural network-based framework

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***Abstract*—Forecasts can help in the decision-making process. Epidemiological forecasts are no different, they can help to evaluate the scenario and possible direction of disease spread, for guiding possible interventions. In this work, Echo State Networks (ESNs) are evaluated for COVID-19 (Coronavirus Disease 2019) cases and deaths forecasting ten days ahead. The chosen locations for the experiment are five states in Brazil, namely Sao Paulo (SP), Bahia (BA), Minas Gerais (MG), Rio de Janeiro (RJ), and Ceara (CE), the states with the most COVID-19 cases as of December 31, 2020. The results are evaluated using performance indexes RMSE (Root-mean-square error), MAE (Mean absolute error), and MAPE (Mean absolute percentage error). Results are compared with a common forecasting technique called ARIMA (Autoregressive Integrated Moving Average). The error signals are compared using Wilcoxon Signed-Rank Test, to evaluate the difference statistically. ESNs presented overall good results for a ten day horizon forecast regarding used performance metrics, but for the number of cases, ARIMA outperformed ESNs regarding RMSE, MAE, and MAPE in all but one state. For the number of deaths however, ESNs outperformed ARIMA in most states when the MAE is taken into account. ESNs are shown to be a solid forecasting model when compared with ARIMA, presenting comparable results and in some cases outperforming it.**

***Index Terms*—Echo state networks, COVID-19, time series, forecasting, ARIMA**

I. INTRODUCTION

By the end of 2019, the world has become aware of a new coronavirus, the Sars-Cov-2 (Severe acute respiratory syndrome coronavirus 2), which causes a potentially lethal severe respiratory syndrome called COVID-19 (Coronavirus Disease 2019), that is specially aggravating in case of comorbidities [1]. Sars-Cov-2 was initially identified in Wuhan, in the province of Hubei, China, and since the identification of the virus and knowledge of the disease, several researchers have worked in multiple knowledge fields to understand the virus spreading and dynamics, the best preventive actions, the medical implications of the disease, possible treatments, and vaccine development. In the fields of computing, mathematics, and statistics, it is no different that a variety of studies have been and are being carried out that could in some way aid in the fight against COVID-19.

Given that forecasts can help decision-making, pandemic predictions can help to plan for problems such as overcrowding of hospital beds, shortage of medical services, and lack of staff. Epidemic forecasts can be challenging as time series carry nonlinearities and present chaotic behavior. Furthermore, the data can be a significant source of uncertainty, as it can contain observational errors [2]. Taking this into account, this paper attempts to contribute by detailing and testing a COVID-19 forecasting framework, applied to five states in Brazil.

Epidemiological forecasting can be done in different forms. Compartmental models, such as SIR (Susceptible-Infectious-Removed-Model), SIRD (Susceptible-Infectious-Recovered-Deceased-Model), and their variants are used [3]–[6] producing accurate results while providing in-depth analysis of the infection spread and its parameters. Another common form is to use time series analysis models as ARIMA (Autoregressive Integrated Moving Average), ETS (Exponential Smoothing State Space model), Holt Winter's Exponential Smoothing, and Assimakopoulos and Nikolopoulos Theta model [7]–[9], which also show promising results. Another approach, the one closer to this paper, involves using Machine Learning models, such as Support Vector Regression, Decision Trees, Random Forest and Neural Networks [10]–[14].

Echo State Networks (ESNs) were shown to provide reliable time-series forecasts in several fields [15]–[19]. In this study ESNs are used to forecast cases and deaths from COVID-19 in five Brazilian states. The models are evaluated using performance indexes (minimization focus) such as RMSE

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(Root-mean-square error), MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error) and compared with the use of ARIMA.

The main contributions of this study are:

1) evaluates the use of ESNs for epidemiological time series forecasting;
2) compares the use of ESNs and ARIMA, evaluating statistical significance between models regarding the errors, using a Wilcoxon Signed-Rank Test;
3) presents a ten days horizon forecast framework for COVID-19 cases and deaths in Brazilian states.

The next sections of this document are organized in the following way. Section II describes of the dataset used for the experiment. Section III outlines the methods used. Section IV describes the framework used in the experiments and the manner in which the tests were conducted. Section V sets out the results achieved. Finally, Section VI presents the conclusions and ideas for future works.

II. Material

The dataset used in this document includes aggregated data on COVID-19 in Brazil from February 25th to December 31st, 2020. Data is collected from state health units every day for all available sites up to the city level by participants in a collaborative project [20]. The full dataset compresses the daily values of new cases, cumulative cases, new deaths, and cumulative deaths caused by COVID-19. In this work, the values for cumulative cases and deaths at the state level were used and limited to the five states with the most cases as of December 31st, 2020. The states are SP (São Paulo), MG (Minas Gerais), BA (Bahia), RJ (Rio de Janeiro), and CE (Ceará). Data was limited to the five states with higher number of incidence as a way to delimit the scope of the paper, and because this five states of the 27 federate units altogether represent more than 39% of cases. Table I presents the main information relating to the data used by the state. Fig. 1 shows where each state is located in Brazil.

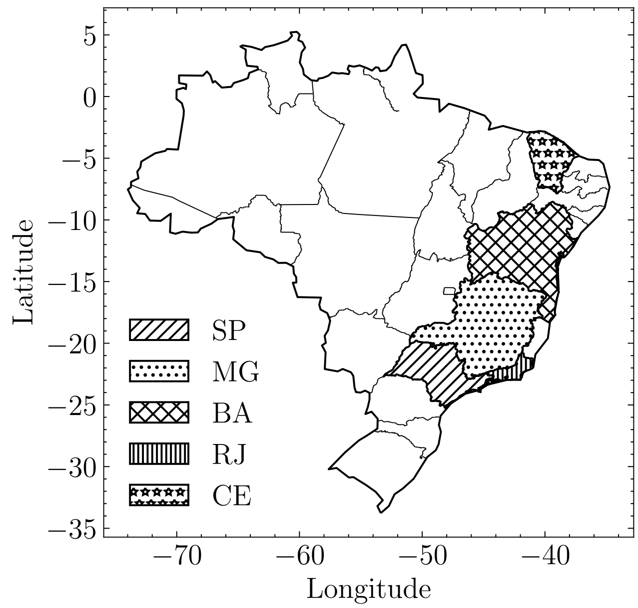

Fig. 1. Brazilian states compressed in the experiment

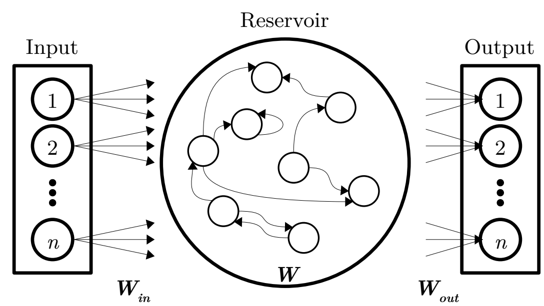

Fig. 2. Diagram of an ESN

III. Methods

In this section the models used in this paper ESN and ARIMA are described.

A. Echo State Networks

ESNs were presented in 2001 by Jaeger [21], but became better known in 2004 through an article by the same author [22]. ESNs are RNNs (Recurrent Neural Networks) with sparse connections within the internal layer, with random weights assigned to those connections. Input layer weights are typically assigned on a random basis. Usually just the output layer is trained, making this optimization problem far simpler. The training can be done using the Moore–Penrose pseudoinverse or with Tikhonov regularized regression (Ridge regression) [23]. Fig. 2 shows a diagram of the ESN.

The main parameters of the reservoir are [24]:

- **sparsity**: relates to how many random connections are in the reservoir, being the ratio of zero elements over the total in the weights matrix.
- **spectral radius** (ρ): the scaling factor of reservoir weights.
- **size**: the number of neurons in the reservoir.

The ESN usually has also a leaking rate (α), which determines how much a past state influences the value of the next state in time. To define the ESN when using Ridge Regression is also necessary a ridge or regularization parameter (λ) for the training of the output layer. The weights of the output layer $\mathbf{W}_{out}$ can be calculated by

$$\mathbf{W}_{out} = \hat{\mathbf{Y}}\mathbf{X}^T \left(\mathbf{X}\mathbf{X}^T + \lambda\mathbf{I}\right)^{-1} \tag{1}$$

where $\hat{\mathbf{Y}}$ is the matrix containing the known values y_t, $\mathbf{X}$ is the matrix with input values and reservoir states, and $\mathbf{I}$ is the identity matrix.

B. Autoregressive Integrated Moving Average

ARIMA is a Box & Jenkins [25] model typically used to deal with non-stationary time series. It is an autoregressive

TABLE I
SUMMARY OF DATASET INFORMATION.

State	Number of Samples	First Report	Cases				Deaths			
			mean	min	max	std	mean	min	max	std
BA	301	2020-03-06	186326,99	1	493400	163785,85	3931,36	0	9129	3286,07
CE	291	2020-03-16	162827,01	9	335992	113064,66	6229,72	0	9993	3605,47
MG	299	2020-03-08	178409,63	1	542909	171296,27	4281,69	0	11902	4088,18
RJ	302	2020-03-05	173134,01	1	434648	135461,88	12169,91	0	25530	8428,85
SP	311	2020-02-25	575771,26	1	1462297	495462,73	21513,76	0	46717	16303,05

model, meaning it is based on the idea that a time series' current states are a function of the series' past p states [26]. Supposing a time series in the form of $\{x_1, x_2, ..., x_t\}$, an ARIMA model can be written as [27]:

$$x_t^d = c+\phi_1 x_{t-1}^d+...+\phi_p x_{t-p}^d+\theta_1\epsilon_{t-1}+...+\theta_q\epsilon_{t-p}+\epsilon_t \quad (2)$$

where θ_i are the moving average parameters, ϕ_i the autoregressive parameters, ϵ the error terms and x_i^d the original time series differentiated d times. The ARIMA model is fully specified by autoregressive (p), differentiation degree (d), and moving average (q) operators, usually written as ARIMA(p, d, q). In general, these parameters are defined by grid-search, autocorrelation and partial autocorrelation functions [25]. When the ARIMA accounts for seasonality it can be referred to as Seasonal ARIMA. The format is so that in the model $ARIMA(p, d, q)(P, D, Q)[m]$ the first parenthesis (p, d, q) represents the parameters for the non-seasonal part of the model, the second part $(P, D, Q)[m]$ represents the seasonal part of the model, m being the frequency established for the seasonality. The absence of the second term indicates that the model doesn't account for seasonality [27].

IV. Framework

The framework consists of three sections: preprocessing, training and evaluation, as depicted in Fig. 3. The code was developed in Python and R languages. The ARIMA implementation that was used for the experiments was from `Fable` R Package [28], using an automatic parameter estimation, while the ESN implementation was from Häußer [29] in the `echos` package, also in R language. The data acquisition, data preprocessing, tests and plots were produced using Python and the packages `matplotlib` [30], `scikit-learn` [31], `pandas` [32] and `numpy` [33].

The steps for producing the results of the experiments in this paper are as follows.

1) The raw time series is first divided into train and test datasets, with the last ten days being separated for testing. All training and fitting procedures for ARIMA and ESN are performed using only the training data.
2) An ESN for each state and every target variable is created and trained. For the ESN seven lags ($n_l = 7$) are used for predictions, so seven past values are used as input for the prediction of the next day. A prediction $\hat{y}$ at time t will take the following form,

$$\hat{y}_t = f(y_{t-1}, ..., y_{t-n_l}, \hat{y}_{t-1}, ..., \hat{y}_{t-n_l}) \quad (3)$$

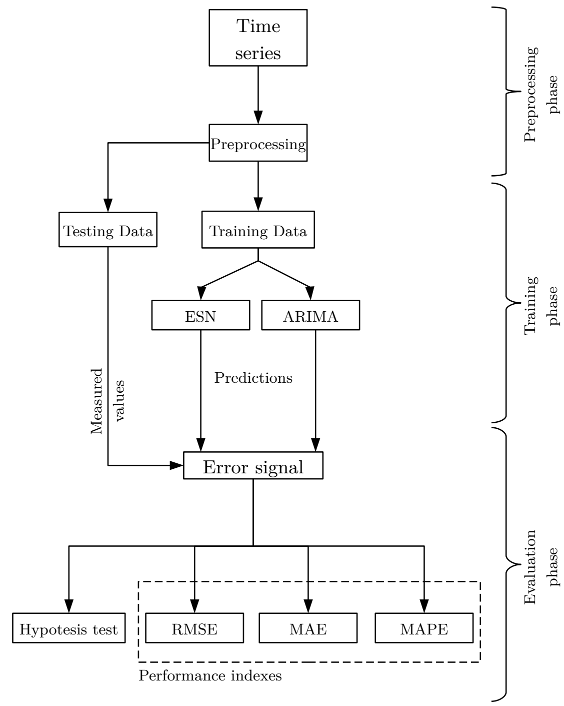

Fig. 3. Flowchart of the proposed methodology

where y_t is a known value and $\hat{y}_t$ is a prediction. Whenever a y_t is available for a moment it is used, *when not* $\hat{y}_t$ is used in its place. So, by the 8-th point in the prediction only past predictions will be used as inputs. The hyperparameters for the ESN are found via gridsearch. Only the ESN that best suited the data is kept.

3) An ARIMA model is also fitted for each state and target. The order of the ARIMA models is determined using a variation of the Hyndman-Khandakar algorithm [34], through the `ARIMA` function from the `Fable` R package [28].
4) Forecasts are produced for the following 10 days for each state and target from ESN and ARIMA models.
5) To evaluate the effectiveness of adopted models and compare them, the metrics RMSE (Root-mean-square error), MAE (Mean absolute error), and MAPE (Mean absolute percentage error) are computed and used as comparison criteria. These errors are defined as

$$\text{RMSE} = \sqrt{\frac{\sum_{n=1}^{N}(\hat{y}_n - y_n)^2}{N}}, \tag{4}$$

$$\text{MAE} = \frac{\sum_{n=1}^{N}|\hat{y}_n - y_n|}{N}, \tag{5}$$

$$\text{MAPE} = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{\hat{y}_n - y_n}{y_n}\right|, \tag{6}$$

where n refers to the n-th data sample, $\hat{y}_n$ is the model estimation for the n-th value and y_n is the known real n-th value.

Moreover, to evaluated statistically the difference between the errors of two forecasting models the pairwise Wilcoxon Signed-Rank Test can be applied. It is a non-parametric test widely employed after the Friedman test, with the purpose to identify significant differences between two sample measurements, or in this paper, the behavior of two forecasting models. In the sequence, some aspects of this test are presented according to the described in [35]. The two-sided hypothesis is given by,

$$H : \begin{cases} H_0 : & \Delta = 0, \\ H_1 : & \Delta \neq 0 \end{cases} \tag{7}$$

where Δ is the variation of differences.

Under the null hypothesis, the models shift in error is not significant (is equal to zero) [36]. Under the alternative hypothesis the location shift is not equal to 0, so the models errors are different pairwise.

6) For every state the model with the best fitness in the test set, regarding MAE is plotted. All errors are presented in Table IV for comparison.

A. Hyperparameters

Table II presents the hyperparameters of the ESNs used to produce the results. These hyperparameters are discovered by gridsearch and are explained in Sec. III-A. The used spectral radius is the one that performed better in the grid search. Most values are smaller than one, as literature suggests it is a good indicator of achieving the echo state propriety. Tasks where long term memory is required usually also call for a higher spectral radius. This can indicate also that the number of cases show a stronger dependency on the recent values.

Table III depicts the parameters for the fitted ARIMA models in each state for the number of cases and deaths. For every state the encountered seasonality was $m = 7$, with the exception of the number of deaths for BA, which showed no clear seasonality. This parameters are not distant from others in recent literature [37], [38], showing low orders for the parameters, specially for the autoregressive parameters p and P. Low p or P indicates lower dependency on past values. d and D indicate the order of differentiation to achieve the proposed ARIMA model. q and Q indicate the order of the moving average component on the model. Because the models are seasonal ARIMA, (0,2,1) show a lot, representing a trend given by a exponential smoothing of previous slopes. Similarly, the form (0, 0, 2) appears significantly in the results, meaning a model in that only the moving average part is taken into account, equivalent to MA(2). It is important to notice that in a seasonal ARIMA model the conjunction of trend and seasonal parameters account for the predictions of the whole phenomenon, complementing each other.

TABLE II
HYPERPARAMETERS FOR ESNS

State	ESN	Size	α	ρ	λ	Density
SP	Cases	200	0.8	0.1	10	0.1
	Deaths	200	0.91	0.1	10	0.1
MG	Cases	200	0.58	0.52	0.24	0.1
	Deaths	200	1	0.1	1.25	0.1
BA	Cases	200	0.61	0.36	1.17	0.1
	Deaths	200	0.29	0.26	4.24	0.1
RJ	Cases	200	0.56	0.1	10	0.1
	Deaths	200	0.61	0.65	10	0.1
CE	Cases	200	0.84	0.1	0.7	0.1
	Deaths	200	0.73	1.22	10	0.1

TABLE III
ARIMA MODEL PARAMETERS

States	**Cases**							**Deaths**						
	p	d	q	P	D	Q	m	p	d	q	P	D	Q	m
SP	1	1	1	0	1	1	7	1	1	2	0	1	2	7
MG	1	1	1	2	1	0	7	1	1	1	0	1	1	7
BA	0	2	1	0	0	2	7	0	2	1	-	-	-	-
RJ	0	2	1	0	0	2	7	1	1	1	0	1	1	7
CE	0	2	1	1	0	1	7	1	2	2	1	0	1	7

V. RESULTS

This section presents the results of the experiments conducted for the out-of-sample test. Data were tested for the last 10 days of collected data. Table I shows the out-of-sample error signals for the models created for each state on the experiment. Figs. 4 - 8 show the results comparing the predictions with the known data samples for the best model of ESN and ARIMA. Only the last four months of data are plotted to facilitate comparison and visualization.

A. São Paulo

For the state of SP regarding the number of cases, the ESN presented a MAE of 7538.23, while ARIMA showed 6562.83. Regarding the number of deaths ESN presented a MAE of 169.34 and ARIMA 193.07, a reduction of 12.24% in MAE.

B. Minas Gerais

For the state of MG the ESN presented a MAE of 2088.39 in the number of cases, while ARIMA gave a MAE of 4122.39. The use of ESN represented a reduction of 49.34% in MAE. In the number of deaths ESN resulted in a MAE of 51.13 and ARIMA of 60.78, a reduction of 15.88%.

TABLE IV
PERFORMANCE METRICS FOR MODELS

State	Metric	Cases		Deaths	
		ESN	ARIMA	ESN	ARIMA
SP	RMSE	8442.37	**7477.63**	**201.57**	227.07
	MAE	7538.23	**6562.83**	**169.34**	193.07
	MAPE	0.53%	**0.46%**	**0.37%**	0.42%
MG	RMSE	**2425.43**	4994.78	**66.48**	77.09
	MAE	**2088.39**	4122.39	**51.13**	60.78
	MAPE	**0.4%**	0.78%	**0.44%**	0.52%
BA	RMSE	6614.05	**6534.67**	**1.41**	5.68
	MAE	5827.98	**5662.76**	**1.14**	5.08
	MAPE	1.2%	**1.16%**	**0.01%**	0.06%
RJ	RMSE	3279.99	**1932.4**	145.37	**143.51**
	MAE	2739.91	**1620.13**	**113.92**	118.57
	MAPE	0.65%	**0.38%**	**0.46%**	0.47%
CE	RMSE	3121.06	**2199.06**	92.99	**61.11**
	MAE	2882.43	**1924.41**	84.76	**55.17**
	MAPE	0.87%	**0.58%**	0.85%	**0.55%**

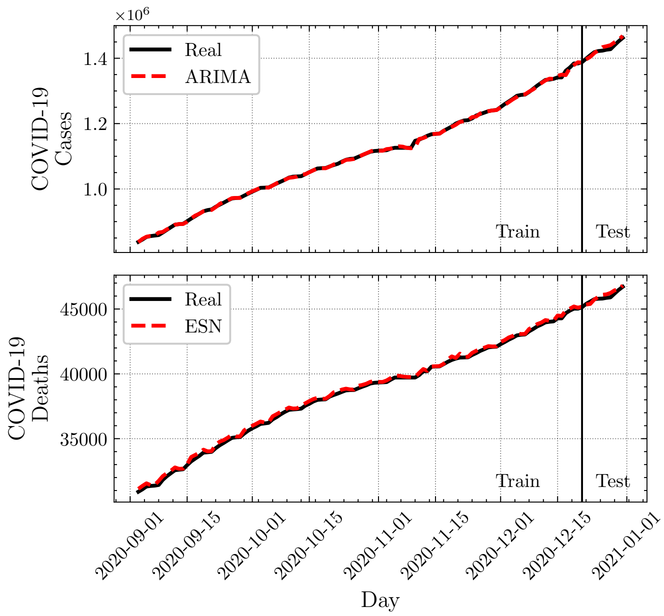

Fig. 4. Measured and predicted values for best performing models in São Paulo

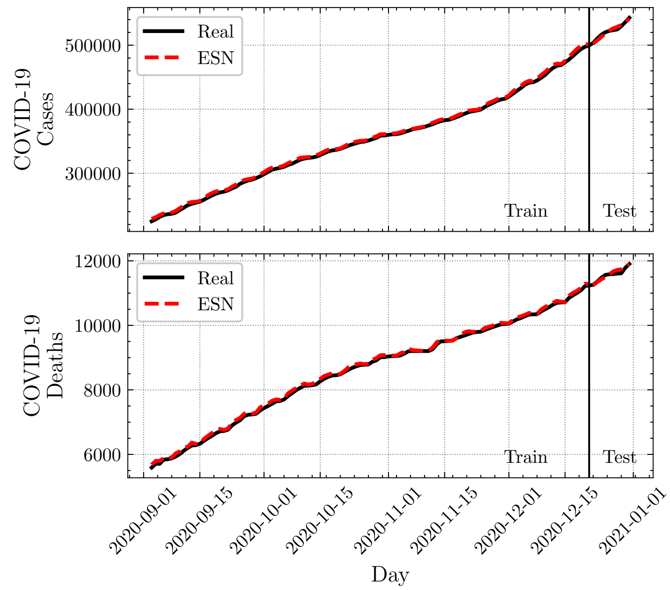

Fig. 5. Measured and predicted values for best performing models in Minas Gerais

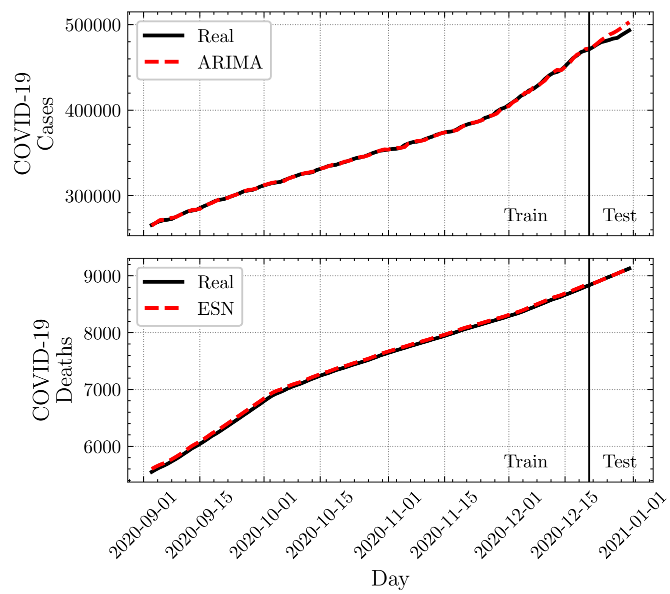

Fig. 6. Measured and predicted values for best performing models in Bahia

C. Bahia

For the state of BA the ESN presented a MAE of 5827.98 when the number of cases is accounted, while ARIMA showed a MAE of 5662.76. For the number of deaths, ESN gave a MAE of 1.14 and ARIMA a MAE of 5.08. Regarding the number of deaths the use of ESNs represented a reduction of 77.56% in MAE.

D. Rio de Janeiro

For the number of cases in the state of RJ, the ESN presented a MAE of 2739.91, while the use of ARIMA presented a MAE of 1620.13, so the use of ESN didn't result in improvement. For the number of deaths ESN showed a MAE of 113.92 and ARIMA 118.57, a reduction of 3.92%.

E. Ceará

For the state of CE, the ESN presented a MAE of 3121.06, and ARIMA of 1924.41, so ARIMA performed better. For the number of deaths, ARIMA also performed better with a MAE of 55.17, while ESNs showed a MAE of 84.76.

F. Error Evaluation

The error for every model was compared, first by visual inspection, from violin plots. The Fig. 9 shows the errors for every model regarding the number of COVID-19 cases, and Fig. 10 shows errors regarding deaths by COVID-19. The error is obtained by the equation $\mathbf{e}_i = y_i - \hat{y}_i$, where y_i is the true

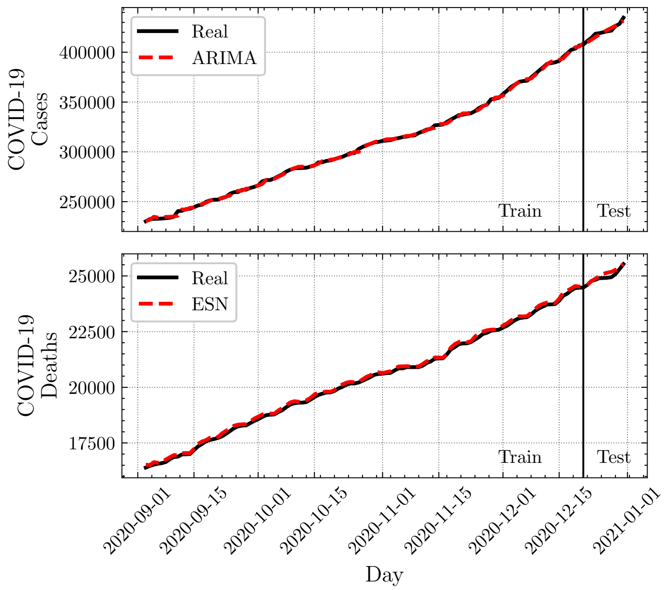

Fig. 7. Measured and predicted values for best performing models in Rio de Janeiro

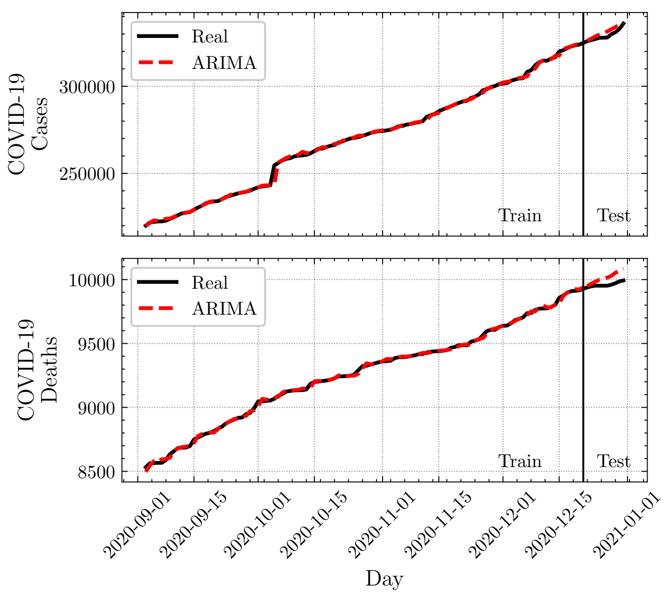

Fig. 8. Measured and predicted values for best performing models in Ceará

value of point i and $\hat{y}_i$ is the predicted value for the same point. By the results in the violin plots it is possible to notice most models are overestimating the number of cases and deaths.

The Wilcoxon test was applied pairwise, the null hypothesis being that the error signals for ARIMA and ESN do not vary, rejecting it means the model showed a significant difference in error. Table V shows the results for the test. The significance adopted was $\alpha = 1\%$, if the p-value is lower the hypothesis is rejected. It is possible to notice that ARIMA and ESN did not show a significant statistical difference for the models used in number of cases for BA and number of deaths in RJ. For all other models H_0 is rejected, meaning their difference in error is significant.

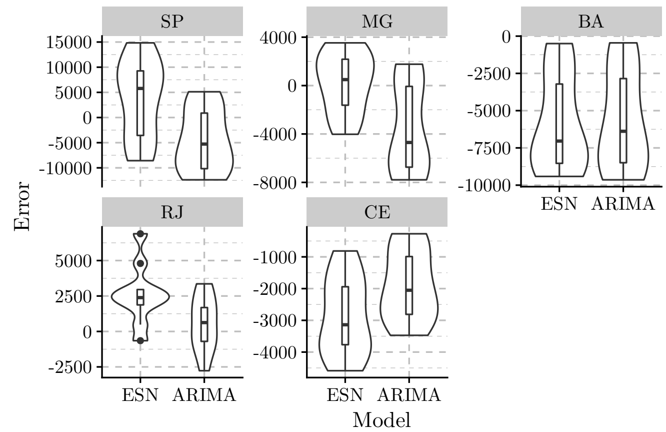

Fig. 9. Violin plot of error signal in the predictions for the **number of cases**.

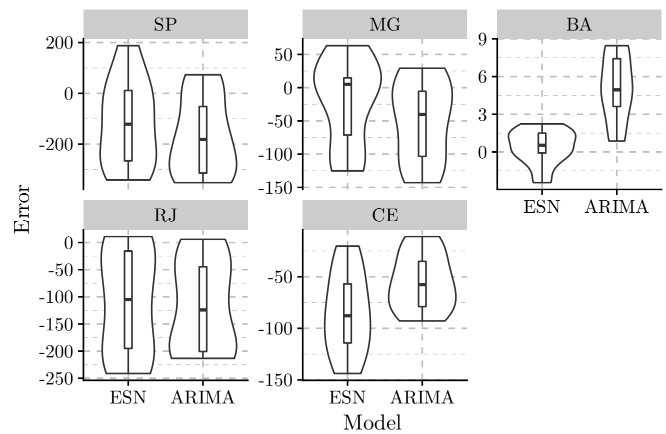

Fig. 10. Violin plot of error signal in the predictions for the **number of deaths**.

TABLE V
WILCOXON TEST RESULTS

State	Target	V-value	p-value	H_0
SP	Cases	55	0,001953125	Rejected
	Deaths	55	0,001953125	Rejected
MG	Cases	55	0,001953125	Rejected
	Deaths	55	0,001953125	Rejected
BA	Cases	15	0,232421875	Accepted
	Deaths	0	0,001953125	Rejected
RJ	Cases	55	0,001953125	Rejected
	Deaths	40	0,232421875	Accepted
CE	Cases	0	0,001953125	Rejected
	Deaths	0	0,001953125	Rejected

VI. CONCLUSION

In this study a framework based on the use of ESNs for time series forecasting was employed. Predictions for ten days ahead COVID-19 cases were presented for each method for each state in the study. Results were compared with the use of a ARIMA model. It is possible to notice that:

- The use of ESNs presented results comparable with ARIMA.
- For the number of cases, ARIMA performed better for most states.
- For the number of deaths, ESN showed better results for most states.

The state of MG was the only one where ESNs showed a better result than ARIMA regarding the number of COVID-19 cases. Regarding the number of deaths, ARIMA performed better just for CE, while ESN achieved better results for every other state when MAE is considered. By visual inspection, ESN performed poorly on the test data in the state of CE, as the ESN predicted a higher number of cases than happened. This may happen because of a conjunction of factors. ESN may not have captured the nonlinearities from the series as well as was expected; the number of deaths may have been reduced by extrinsic factors, as state intervention on lockdown policies and new heath interventions; or even a change in how data was collected. A possibility for the cases where ESNs didn't perform as well as ARIMA is that the selected parameters via grid-search were not optimal, so finding another tuning framework using metaheuristics can improve these results. The use of cumulative cases and deaths introduces a trend in the development of the series. The comparison with MAE and RMSE would be the same using new cases and new deaths day-by-day, but models could perform differently fitting in this values directly, and this can also be a source of error in this paper. The smaller values of spectral radius of the ESNs fitted for the number of cases can show a dependency on the recent values, thus performing worst when not taking into account the older values as much as new ones. The greater ρ for the state of MG, with ESNs performing better for number of cases, shows how this can be an indicator of the problem for the ESNs used for the other states. Increasing the spectral radius manually can be a strategy to try and overcome this problem. Another possible strategy can be to use metaheuristics to select them, rather then grid search.

For future research it is intended to: (i) ensemble different predictions from different ESNs, as each reservoir has slightly different predictions, so generating multiple ESNs may improve results by Bootstrap Aggregation; (ii) make use of other Machine Learning methods and Stack them; (iii) test decomposition methods such as Singular Spectrum Analysis, Variational Mode Decomposition, and Wavelet Transforms; (iv) implement a different hyperparameter selection framework using metaheuristics; and (v) use detrended series and daily new cases and deaths directly. Also for future research, it is possible to compare the results of ARIMA, ESN and other machine learning methods to epidemiological models, evaluating their performance and possibly bringing together the best parts of each model.

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