

Oceanic Niño Index forecasting based on dynamic ensemble selection

Jair Paulino de Sales

Centro de Informática, Universidade Federal de Pernambuco

Recife - PE, Brazil

jps4@cin.ufpe.br

José Eduardo de Carvalho Lima

Centro Universitário Dr. Leão Sampaio

Juazeiro do Norte - CE, Brazil

joseeduardo@leaosampaio.edu.br

Paulo S. G. de Mattos Neto

Centro de Informática, Universidade Federal de Pernambuco

Recife - PE, Brazil

psgmn@cin.ufpe.br

Paulo R. Alves Firmino

Centro de Ciências e Tecnologia, Universidade Federal do Cariri

Juazeiro do Norte - CE, Brazil

paulo.firmino@ufca.edu.br

ABSTRACT

El Niño Southern Oscillation (ENSO) events have a significant impact on the global climate, leading to various consequences such as droughts. These events are closely intertwined with multiple aspects of health, agriculture, and economics. Therefore, accurate forecasting of ENSO events is crucial in mitigating their impacts. In recent literature, multiple predictor systems (MPS) methods, including Dynamic Ensemble Selection (DES), have gained prominence due to their ability to enhance overall forecasting accuracy. However, despite being a promising alternative, there is a lack of studies focusing on ENSO-related time series forecasting using DES methods. Hence, this research aims to analyze the performance of a DES method in one-step ahead forecasting of the Oceanic Niño Index (ONI) time series. Based on the presented results, the DES method demonstrated superior performance compared to the alternative methods implemented in this study across the established performance measures.

KEYWORDS. Dynamic selection. Multiple predictor systems. Euclidean distance. ENSO.

Paper topics: IC - Computational intelligence. AGMA - OR in Agriculture and Environment

RESUMO

A ocorrência do El Niño Oscilação Sul (ENSO) tem um impacto significativo no clima global, resultando em diversas consequências, como secas. Esses eventos estão intimamente relacionados a múltiplos aspectos da saúde, agricultura e economia. Portanto, a previsão precisa desses é crucial para mitigar seus impactos. Na literatura recente, sistemas de múltiplos preditores (MPS),

incluindo os métodos classificados como Dynamic Ensemble Selection (DES), ganharam destaque devido à sua capacidade de aprimorar a precisão geral das previsões. No entanto, apesar de ser uma alternativa promissora, existe uma escassez de estudos que se concentrem na previsão de séries temporais relacionadas ao ENSO usando métodos DES. Portanto, esta pesquisa tem como objetivo analisar o desempenho de um método DES na previsão um passo à frente da série temporal do Oceanic Niño Index (ONI). Com base nos resultados apresentados, o método DES demonstrou um desempenho superior em comparação aos métodos alternativos implementados, considerando as medidas de desempenho estabelecidas.

PALAVRAS CHAVE. Seleção dinâmica. Sistemas de múltiplos preditores. Distância Euclidiana. ENSO.

Tópicos: IC - Inteligência Computacional. AGMA - PO na Agricultura e Meio Ambiente

1. Introduction

El Niño Southern Oscillation (ENSO) arises from an intense mutual interaction between the ocean and atmosphere in tropical region of the Pacific Ocean and tends to occur every three to five years [Philander, 1989; Wang et al., 2021]. Specifically, a ENSO event occurs when the 3-month running mean of sea surface temperature (SST) anomalies in the Niño 3.4 region, known as Oceanic Niño Index (ONI), is above (below) the threshold of $+0.5^{\circ}\text{C}$ (-0.5°C) for at least 5 consecutive months [Huang et al., 2017; Mu et al., 2019; NOAA, 2023]. A warm ENSO period is commonly known as El Niño, while a cold period is known as La Niña.

ENSO events can have a significant impact on climate around the world, ranging from droughts [Vicente-Serrano et al., 2011, 2017] to floods [Yan et al., 2020; Saghaian et al., 2017]. Besides, there are studies that assess the impact of ENSO on health [Kovats et al., 2003; Pramanik et al., 2020], agriculture [Li et al., 2020], and economics [Generoso et al., 2020; Atems e Sardar, 2021]. Hence, as described by Wang et al. [2021], accurate prediction of ENSO events can aid in reducing their impacts.

There are four commonly employed ENSO forecast strategies: dynamical models, classical statistical methods, hybrid dynamical-statistical models, and machine learning (ML) methods [Wang et al., 2021]. Dynamical models are constructed by formulating mathematical equations based on the laws of physics to effectively represent the interaction between the ocean and atmosphere [Stockdale et al., 2011]. In contrast, statistical models employ datasets of ENSO-related indexes, such as ONI, to develop predictive models. In this case, the time series resulting from these models can help in understanding the future behavior of ENSO [Alexander et al., 2008]. In turn, the hybrid dynamical-statistical models combine both previously mentioned strategies [Zhang et al., 2017].

Lastly, ML methods have emerged as prominent approaches in recent years. In these cases, ENSO-related time series can be modeled in order to predict sequential future values [Wang et al., 2021; Lins et al., 2013; Mattos Neto et al., 2022]. The most common ML approach involves a single method (e.g., such as support vector regressor - SVR [Lins et al., 2013], artificial neural networks - ANN [Dijkstra et al., 2019]) to predict a specific time series. Otherwise, multiple predictor systems (MPS) methods have gained prominence in the literature once improve the overall forecasting accuracy [Wang et al., 2021; Mattos Neto et al., 2022; Mu et al., 2019].

Furthermore, Dynamic Ensemble Selection (DES) approaches can be considered as a specific instance MPS, where each individual model specializes in capturing a specific pattern within the time series data [Silva et al., 2021]. Thus, instead of combining all trained models, DES methods dynamically select the n models that specialize in a given test pattern to be predicted [Yao et al., 2019]. This forecasting alternative is useful for forecasting real-world time series once adapts the ensemble by selecting the most suitable models to each test pattern. However, despite being a promising alternative, no studies have been identified involving the forecasting of time series associated with ENSO using DES methods.

Given the aforementioned context, this paper aims to analyze the performance of a DES method in forecasting (one-step ahead) the time series of the ONI index. The paper is structured as follows: Section 2 presents a literature review. Subsequently, Section 3 describes the experimental protocol conducted in this study. Section 4 presents the results and discussion of each implemented model and compares them with the DES approach. Finally, Section 5 concludes with the final remarks of this paper.

2. Literature review

Initially, this session presents the classical and ML models used to forecasting time series. Following, the DES methods are also discussed.

2.1. Classical models

The Autoregressive Integrated Moving Average (ARIMA) model predicts the value of a time series as a linear combination of its past values and previous model residuals. The ARIMA (p, d, q) is a combination of the Autoregressive (AR), Moving Averages (MA) models, and a stationarity step, in which p denotes the numbers of autoregressive terms, d is the number of times that the series must be differentiated until becoming nearly stationary, and q implies the number of moving average terms [Cryer e Chan, 2008]. Given a time series $\{Z_t : 1 \leq t \leq n\}$, mathematically the ARIMA (p, d, q) model is written as:

$$\phi(B)(1 - B)^d z_t = \theta(B)\varepsilon_t \quad (1)$$

in which t represents the time index, z_t is the value of the time series observation at time t , B is the backshift operator, such that $Bz_t = z_{t-1}$, and ε_t is a series of random shocks. In equation 1, $\phi(B)$ is the autoregressive operator, represented as a polynomial in the backshift operator B , which is defined as:

$$\phi(B) = 1 - \phi_1 B - \dots - \phi_p B^p \quad (2)$$

and $\theta(B)$ is the moving-average operator, represented as a polynomial in the backshift operator B , which is defined as:

$$\theta(B) = 1 - \theta_1 B - \dots - \theta_q B^q \quad (3)$$

In turn, the Exponential Smoothing (ETS) formalism assigns exponentially decreasing weights to the previous time series values as the observation becomes old, i.e. recent observations might receive relatively greater weight in the forecast than older ones [Gardner Jr, 2006]. Smoothing models are based on assumptions that time series are constructed from unobserved components such as level, trend, and seasonal effects. These components must be adjusted over time to follow the demand pattern [Wu et al., 2016]. The acronym ETS refers to both Exponential Smoothing and the components of Error (E), Trend (T), and Seasonality (S), which define a model within the ETS family.

The state space model is a more sophisticated stochastic concept than the exponential smoothing method. Every exponential smoothing method corresponds to two possible state space models, one with additive errors and the other with multiplicative errors. Since there are 15 exponential smoothing methods, 30 state space models are deduced accordingly. Then a linear innovations state space model can be written as

$$y_t = w'x_{t-1} + \varepsilon_t \quad (4)$$

in which

$$x_t = Fx_{t-1} + g\varepsilon_t \quad (5)$$

where ε_t is a white noise series and F , g , and w are coefficients. Equation 4 is known as the measurement (or observation) equation; it describes the relationship between the unobserved states x_{t-1} and the observation y_t . Equation 5 is known as the transition (or state) equation; it describes the evolution of the states over time.

2.2. ML models

In time series forecasting problems, SVR and ANN are prominent and commonly used methods. Specifically, the Multilayer Perceptron (MLP) [Haykin e Network, 2004], Extreme Learning Machines (ELM) [Huang et al., 2006], and Long Short-Term Memory (LSTM) [Greff et al., 2016] networks are renowned ANN architectures. Within this class of models, it is necessary to perform a preprocessing step to transform the time series into a dataset that can be read and modeled. Common preprocessing steps include: (i) splitting the data into training, validation, and testing sets; (ii) normalizing or standardizing the data; and (iii) applying time windowing to the time series [Silva et al., 2021].

2.3. Dynamic selection approaches

In the context of time series, MPS has caught the attention of researchers due to the promising results that have been presented in recent years [Mattos Neto et al., 2022]. Commonly, the implementation of a MPS considers three main stages: Generation, Selection, and Integration (also known as Combination) [Yao et al., 2019; Silva et al., 2021]. Initially, in the Generation phase, a pool of models is trained based on a the training dataset. The pool is defined as homogeneous if only models of the same formalism are used. On the other hand, if different formalisms are used, the pool is classified as heterogeneous. It is known that diverse and accurate pools built with models that capture different patterns tend to positively affect the quality of MPS forecasts.

Secondly, in the Selection phase, one or more models are selected based on a specific criterion. The selection can occur during model training (offline), meaning that some strategy is used to select the best models at the moment they are being trained. It is important to note that the selection strategy adopted is closely associated with the computational cost of the MPS [Silva et al., 2020]. Finally, in the Integration phase, the predictions are made based on the previously selected models and using some method of combination.

In this scenario, instead of using the same model for making predictions, dynamic selection approaches aim to select the best models for each new test pattern [Yao et al., 2019; Yankov et al., 2006; Widodo e Budi, 2011]. Nonetheless, the dynamic selection of the best models is a complex task once there is no well-established criterion on how to execute it [Widodo e Budi, 2011; Silva et al., 2021].

The DES proposed in this paper, named herein as Dynamic Ensemble Selection by Local Accuracy (DES-LA), is based on Silva et al. [2021]. Dynamic selection approaches assumes that the most suitable models to forecast the future value z_{t+1} , given its time window ($w_t = z_t, z_{t-1}, z_{t-2}, \dots, z_{t-n-1}$) with n lags, is the models with the best performances in the neighborhood of w_t . Here, the performance of the models are calculated based on the Root Mean Square Error (RMSE, Eq. 6). Thus, this neighborhood, the Region of Competence (RoC), is composed of k time windows from the validation set most similar to w_t . The use of the Euclidean distance as similarity measure to create the RoC is a well-known strategy [Silva et al., 2020]. Finally, the best m models are combined based on combination method (e.g. average, median or mode). The parameters k , m and combination method can be selected based on a search strategy.

3. Experimental protocol

Initially, the ONI time series was obtained from the National Oceanic Atmospheric Administration website [NOAA, 2023]. It has 879 monthly observations ranging from March 1950 to May 2023. Next, in the preprocessing phase, the data was divided into training, validation, and test sets considering the proportions of 50%, 25%, and 25%, respectively [Silva et al., 2021]. Subsequently, the sets were normalized to the interval $[0.1; 0.9]$ based on the minimum and maximum values from the training and validation sets [Mattos Neto et al., 2022]. Furthermore, the sliding

window algorithm [Suresh et al., 2020] was applied to convert the data from the time series format to a table, enabling the training of the ML models. In this case, the lag size was estimated based on the partial autocorrelation function (PACF) [Mattos Neto et al., 2022].

Following, regarding the training phase of the single models, the classical forecasting approaches, ARIMA and ETS, were trained without a validation phase (the parameters were estimated based on the concatenation of the training and validation sets). In these cases, the `Forecast R` package [Hyndman et al., 2020] was applied. In turn, the parameters of the ML models (SVR, ELM, MLP, and LSTM) were estimated through the execution of the grid search algorithm [Alsharef et al., 2022]. The grid parameters used to train SVR, MLP, and LSTM models are based on Oliveira et al. [2021], and the R packages are, respectively, `e1071` [Meyer et al., 2023], and `tensorflow` [Fabel et al., 2022]. In the case of the ELM model, the parameters used were based on Castillo-Botón et al. [2020] and the R package was `elmNNRcpp` [Mouselimis et al., 2022].

In order to increase the number of single models to be combined, it was decided to generate 160 ELM models from different parameters combinations. Therefore, there is a pool constructed by considering different models (heterogeneous pool). This alternative was developed with the aim of increasing the number of patterns to be identified by the single models. As a result, the combined models tend to exhibit better performance.

Regarding the ensemble methods applied in the pool, first, two ‘non-parametric’ approaches were developed: ensemble based on simple average (eSA) and ensemble based on median (eSM). Thus, the DES-LA was applied. Its parameters were selected based a grid search (k , n , ensemble method).

Tabela 1: Grid search parameters by model for studying ENSO time series.

Model	Parameters	Values
SVR [Oliveira et al., 2021]	Kernel	Radial, Sigmoid
	Gamma	1, 0.1, 0.001, 0.001
	Cost	0.1, 1, 10, 100, 1000, 10000
	Epsilon	0.1, 0.01, 0.001
	Tolerance	0.001
ELM [Castillo-Botón et al., 2020]	Activation function	ReLU, Sigmoid, Radial
	Units in hidden layer	50, 75
MLP [Oliveira et al., 2021]	Activation function	Sigmoid
	Units in hidden layer	2, 5, 10, 15, 20
	Algorithm	Adam
LSTM [Oliveira et al., 2021]	Units in hidden layer	2, 5, 10, 15, 20
	Algorithm	Adam
DES-LA	k	20, 30, 40
	m	1, 5, 10, 15, 20, 25
	Combination method	Median, Mean, Mode
	Distance	Euclidean

Four well-know performance measures were used to evaluate single and ensemble models: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error, and Theil’s U (Equations 6, 7, 8, and 9). In which, z_t is the value of the time series at t , $\hat{z}_t$ is the respective forecast, and N is the number of samples taken into account.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (z_t - \hat{z}_t)^2}, \quad (6)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |z_t - \hat{z}_t|, \quad (7)$$

$$MAPE = \frac{100}{N} \sum_{t=1}^N \left| \frac{z_t - \hat{z}_t}{z_t} \right| \quad (8)$$

$$\text{Theil's } U = \frac{\sum_{t=1}^N (z_t - \hat{z}_t)^2}{\sum_{t=1}^N (z_t - z_{t-1})^2}, \quad (9)$$

These performance measures make easier to evaluate the models across multiple aspects. RMSE and MAE provide error measures in the same unit as the time series, thus aiding in their interpretability. In turn, Theil's U compares the models with a naive model. If Theil's U < 1 (Theil's U > 1), the models is better (worse) than naive predictor.

Lastly, the Diebold-Mariano (DM) statistical test was conducted on the residuals of the models to determine whether there are significant statistical differences between the performance of DES and alternative approaches. The null hypothesis of the DM test states that both models have similar prediction performances. Conversely, the alternative hypothesis suggests that there is a difference in the forecasting performance between the models. A significance level of 5% was employed.

All experiments were conducted considering one-step ahead forecasts.

4. Results and discussion

Table 2 presents the selected parameters, taking into account the training phase for the classical models (ARIMA and ETS), and the training/validation phase for the ML models (ELM, SVR, MLP, and LSTM). It can be observed that the classical models were not able to predict seasonality. In the case of ARIMA, the model only takes into account the last three observations to make its forecasts. In the case of ETS, only additive error and trend are considered. Further, ML models also did not capture seasonality. In these cases, the lag parameter was estimated based on the PACF, and its value was determined to be 5. In the case of DES-LA, the selected parameters indicate that the method considers a region of competence built with the 30 most similar instances to the test pattern, and the forecast will be based on the median combination of the 15 best models.

Tabela 2: Selected parameters taking into account the training phase (ARIMA and ETS) or training and validation (ELM, SVR, MLP, and LSTM) for forecasting ENSO time series. Lag parameter was selected based on the PACF.

Model	Selected parameters
ARIMA	ARIMA(3,0,0)
ETS	ETS(A,A,N)
ELM	Lag=5, Activation function=Sig, Units in hidden layer=75
SVR	Lag=5, Kernel=Radial, Gamma=0.001, Cost=1000, Epsilon=0.001, Tolerance=0.001
MLP	Lag=5, Activation function=Sigmoid, Units in hidden layer=2, Algorithm=Adam
LSTM	Lag=5, Units in hidden layer=5, Algorithm=Adam
DES-LA	k=30, n=15, Combination method=Median

Tabela 3: Performance measures for single and ensemble models when forecasting ENSO time series.
Highlighted values indicate better performance.

Model	RMSE	MAE	MAPE	Theil's U
ARIMA	0.1200	0.0983	26.66	0.3431
ETS	0.1348	0.1082	28.23	0.4325
ELM	0.1235	0.1005	27.28	0.3624
SVR	0.1221	0.0996	27.21	0.3544
MLP	0.1228	0.0985	25.89	0.3594
LSTM	0.1223	0.1011	27.67	0.3554
eSA	0.1108	0.0903	25.40	0.2920
eSM	0.1126	0.0921	25.96	0.3014
DES-LA	0.1086	0.0874	24.65	0.2805

Table 3 presents the RMSE, MAE, MAPE, and Theils' U values to single and ensemble methods. The ARIMA model was the best among the single alternatives regarding RMSE, MAE, and Theil's U. On the other hand, the MLP model was the best among the single ones regarding MAPE. The ETS model had the worst performance across all analyzed measures. Furthermore, across all alternatives, the DES-LA method consistently achieved superior results in all the performance measures used. However, it should be noted that the other ensemble models (eSA and eSM) outperformed the single alternatives. This result highlights the fact that the strategy adopted for constructing a heterogeneous pool contributed to the successful performance of the combined models.

Figure 1 shows the last 30 observations of the ONI time series (test set) and the forecasts from the best model (DES-LA, indicated in blue), the second-best model (cSA, indicated in red) and pool of models (indicated in gray). Two relevant points should be highlighted: the first is that the red line (cSA model) tends to underestimate the original series, as it tends to have values below the blue line (DES-LA model). This behavior occurs not only in the last 30 observations shown in the Figure but throughout the entire test set. Secondly, the pool of models (in gray) exhibits low variability. Although the combined methods tend to perform well, this could be further improved if the created pool were more diverse.

Table 4 presents the statistical comparison between DES-LA and other models according to Diebold-Mariano test. At a significance level of 5%, the null hypothesis is rejected, confirming that the performance of DES-LA was superior to that of the alternative approaches. The cSA method was the most competitive; however, the DES-LA method still achieved superior performance ($p = 4.5\%$).

Tabela 4: P-values for the Diebold-Mariano test between the DES-LA and other models when forecasting ENSO time series.

ARIMA	ETS	ELM	SVR	MLP	LSTM	eSA	eSM
<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.045	0.004

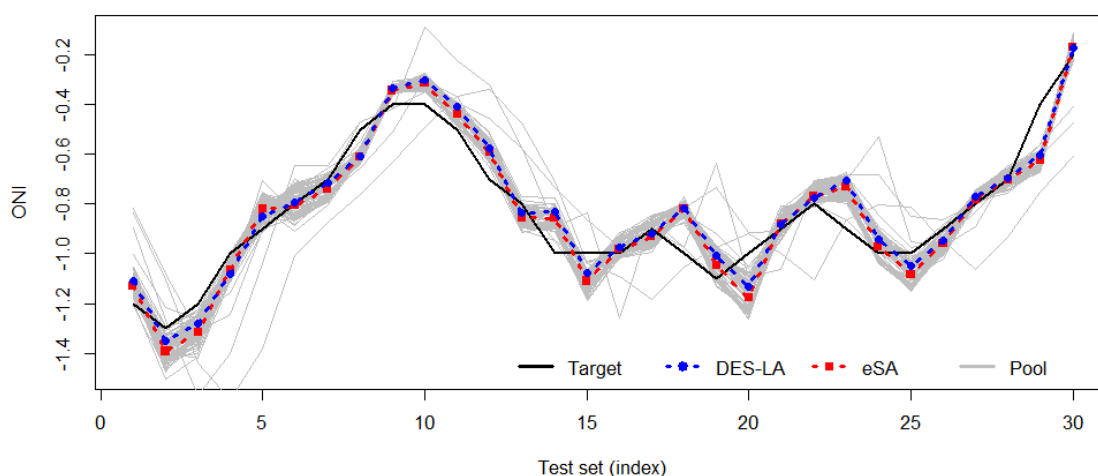


Figura 1: ONI time series (last 30 observation of test set) and the forecasts from the best model (DES-LA, indicated in blue), the second-best model (eSA, indicated in red) and pool of models (indicated in gray).

5. Conclusion

This paper has presented an application of DES-LA method, a dynamic selection system, for forecasting the time series of the ONI index using a heterogeneous pool. The DES-LA method exhibited superior results in comparison to the implemented alternatives for all calculated performance measures. In addition, DES-LA performed better at a statistical level regarding Diebold-Mariano test for a significance level of 5%. Future research involves: 1) the use of other similarity measures to build the region of competence; 2) development of strategies to increase pool diversity; 3) selection of the best methods based on statistical information from the time series; and 4) perform medium and long-term forecasts.

Referências

- Alexander, M. A., Matrosova, L., Penland, C., Scott, J. D., e Chang, P. (2008). Forecasting pacific ssts: Linear inverse model predictions of the pdo. *Journal of Climate*, 21(2):385–402.
- Alsharef, A., Aggarwal, K., Sonia, Kumar, M., e Mishra, A. (2022). Review of ml and automl solutions to forecast time-series data. *Archives of Computational Methods in Engineering*, 29(7): 5297–5311.
- Atems, B. e Sardar, N. (2021). Exploring asymmetries in the effects of el niño-southern oscillation on us food and agricultural stock prices. *The Quarterly Review of Economics and Finance*, 81: 1–14.
- Castillo-Botón, C., Casillas-Pérez, D., Casanova-Mateo, C., Moreno-Saavedra, L., Morales-Díaz, B., Sanz-Justo, J., Gutiérrez, P. A., e Salcedo-Sanz, S. (2020). Analysis and prediction of dammed water level in a hydropower reservoir using machine learning and persistence-based techniques. *Water*, 12(6):1528.

- Cryer, J. D. e Chan, K.-S. (2008). *Time series analysis: with applications in R*. Springer Science & Business Media.
- Dijkstra, H. A., Petersik, P., Hernández-García, E., e López, C. (2019). The application of machine learning techniques to improve el niño prediction skill. *Frontiers in Physics*, p. 153.
- Falbel, D., Allaire, J., Tang, Y., Eddelbuettel, D., Golding, N., e Kalinowski, T. *tensorflow: R Interface to TensorFlow*, 2022. URL <https://cran.r-project.org/web/packages/tensorflow/index.html>. R package version 2.11.0.
- Gardner Jr, E. S. (2006). Exponential smoothing: The state of the artâpart ii. *International journal of forecasting*, 22(4):637–666.
- Generoso, R., Couharde, C., Damette, O., e Mohaddes, K. (2020). The growth effects of el nino and la nina: Local weather conditions matter. *Annals of Economics and Statistics*, (140):83–126.
- Greff, K., Srivastava, R. K., Koutník, J., Steunebrink, B. R., e Schmidhuber, J. (2016). Lstm: A search space odyssey. *IEEE transactions on neural networks and learning systems*, 28(10): 2222–2232.
- Haykin, S. e Network, N. (2004). A comprehensive foundation. *Neural networks*, 2(2004):41.
- Huang, B., Thorne, P. W., Banzon, V. F., Boyer, T., Chepurin, G., Lawrimore, J. H., Menne, M. J., Smith, T. M., Vose, R. S., e Zhang, H.-M. (2017). Extended reconstructed sea surface temperature, version 5 (ersstv5): upgrades, validations, and intercomparisons. *Journal of Climate*, 30 (20):8179–8205.
- Huang, G.-B., Zhu, Q.-Y., e Siew, C.-K. (2006). Extreme learning machine: theory and applications. *Neurocomputing*, 70(1-3):489–501.
- Hyndman, R. J., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O’Hara-Wild, M., Petropoulos, F., Razbash, S., e Wang, E. (2020). Package forecast. *Online]* <https://cran.r-project.org/web/packages/forecast/forecast.pdf>.
- Kovats, R. S., Bouma, M. J., Hajat, S., Worrall, E., e Haines, A. (2003). El niño and health. *The Lancet*, 362(9394):1481–1489.
- Li, Y., Strapasson, A., e Rojas, O. (2020). Assessment of el niño and la niña impacts on china: Enhancing the early warning system on food and agriculture. *Weather and Climate Extremes*, 27: 100208.
- Lins, I. D., Araujo, M., das Chagas Moura, M., Silva, M. A., e Droguett, E. L. (2013). Prediction of sea surface temperature in the tropical atlantic by support vector machines. *Computational Statistics & Data Analysis*, 61:187–198.
- Mattos Neto, P. S. d., Cavalcanti, G. D., de O Santos Júnior, D. S., e Silva, E. G. (2022). Hybrid systems using residual modeling for sea surface temperature forecasting. *Scientific Reports*, 12 (1):1–16.

- Meyer, D., Dimitriadou, E., Hornik, K., Weingessel, A., Leisch, F., Chang, C.-C., e Lin, C.-C. *e1071: Misc Functions of the Department of Statistics, Probability Theory Group (Formerly: E1071), TU Wien*, 2023. URL <https://cran.r-project.org/web/packages/e1071/index.html>. R package version 1.7-13.
- Mouselimis, L., Gosso, A., e Jonge, E. d. *elmNNRcpp: The Extreme Learning Machine Algorithm*, 2022. URL <https://cran.r-project.org/web/packages/elmNNRcpp/index.html>. R package version 1.0.4.
- Mu, B., Peng, C., Yuan, S., e Chen, L. (2019). Enso forecasting over multiple time horizons using convlstm network and rolling mechanism. In *2019 international joint conference on neural networks (ijcnn)*, p. 1–8. IEEE.
- NOAA, N. O. A. A. (2023). Cold and warm episodes by season. https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php. Accessed: 2023-05-01.
- Oliveira, J. F. d., Silva, E. G., e de Mattos Neto, P. S. (2021). A hybrid system based on dynamic selection for time series forecasting. *IEEE Transactions on Neural Networks and Learning Systems*, 33(8):3251–3263.
- Philander, S. G. (1989). El niño, la niña, and the southern oscillation. *International geophysics series*, 46:X–289.
- Pramanik, M., Singh, P., Kumar, G., Ojha, V. P., e Dhiman, R. C. (2020). El niño southern oscillation as an early warning tool for dengue outbreak in india. *BMC public health*, 20:1–11.
- Saghaian, B., Haghnegahdar, A., e Dehghani, M. (2017). Effect of enso on annual maximum floods and volume over threshold in the southwestern region of iran. *Hydrological sciences journal*, 62(7):1039–1049.
- Silva, E. G., Cavalcanti, G. D., de Oliveira, J. F. L., e de Mattos Neto, P. S. (2020). On the evaluation of dynamic selection parameters for time series forecasting. In *2020 International Joint Conference on Neural Networks (IJCNN)*, p. 1–7. IEEE.
- Silva, E. G., Neto, P. S. D. M., e Cavalcanti, G. D. (2021). A dynamic predictor selection method based on recent temporal windows for time series forecasting. *IEEE Access*, 9:108466–108479.
- Stockdale, T. N., Anderson, D. L., Balmaseda, M. A., Doblas-Reyes, F., Ferranti, L., Mogensen, K., Palmer, T. N., Molteni, F., e Vitart, F. (2011). Ecmwf seasonal forecast system 3 and its prediction of sea surface temperature. *Climate dynamics*, 37:455–471.
- Suresh, V., Janik, P., Rezmer, J., e Leonowicz, Z. (2020). Forecasting solar pv output using convolutional neural networks with a sliding window algorithm. *Energies*, 13(3):723.
- Vicente-Serrano, S. M., Aguilar, E., Martínez, R., Martín-Hernández, N., Azorin-Molina, C., Sánchez-Lorenzo, A., El Kenawy, A., Tomás-Burguera, M., Moran-Tejeda, E., López-Moreno, J. I., et al. (2017). The complex influence of enso on droughts in ecuador. *Climate Dynamics*, 48:405–427.

- Vicente-Serrano, S. M., López-Moreno, J. I., Gimeno, L., Nieto, R., Morán-Tejeda, E., Lorenzo-Lacruz, J., Beguería, S., e Azorin-Molina, C. (2011). A multiscalar global evaluation of the impact of enso on droughts. *Journal of Geophysical Research: Atmospheres*, 116(D20).
- Wang, S., Mu, L., e Liu, D. (2021). A hybrid approach for el niño prediction based on empirical mode decomposition and convolutional lstm encoder-decoder. *Computers & Geosciences*, 149: 104695.
- Widodo, A. e Budi, I. (2011). Model selection for time series forecasting using similarity measure. In *2011 International Conference on Advanced Computer Science and Information Systems*, p. 221–226. IEEE.
- Wu, L., Liu, S., e Yang, Y. (2016). Grey double exponential smoothing model and its application on pig price forecasting in china. *Applied Soft Computing*, 39:117–123.
- Yan, Y., Wu, H., Gu, G., Ward, P. J., Luo, L., Li, X., Huang, Z., e Tao, J. (2020). Exploring the enso impact on basin-scale floods using hydrological simulations and trmm precipitation. *Geophysical Research Letters*, 47(22):e2020GL089476.
- Yankov, D., DeCoste, D., e Keogh, E. (2006). Ensembles of nearest neighbor forecasts. In *Machine Learning: ECML 2006: 17th European Conference on Machine Learning Berlin, Germany, September 18-22, 2006 Proceedings 17*, p. 545–556. Springer.
- Yao, C., Dai, Q., e Song, G. (2019). Several novel dynamic ensemble selection algorithms for time series prediction. *Neural Processing Letters*, 50:1789–1829.
- Zhang, W., Villarini, G., Slater, L., Vecchi, G. A., e Bradley, A. A. (2017). Improved enso forecasting using bayesian updating and the north american multimodel ensemble (nmme). *Journal of Climate*, 30(22):9007–9025.