

12th Seminar for Homogenization and Quality Control in Climatological Databases and the 7th Interpolation Conference, followed by the Danube-Adapt Project meeting.



WORLD
METEOROLOGICAL
ORGANIZATION

Reconstruction of Maximum Temperature Time Series Using Machine Learning Models



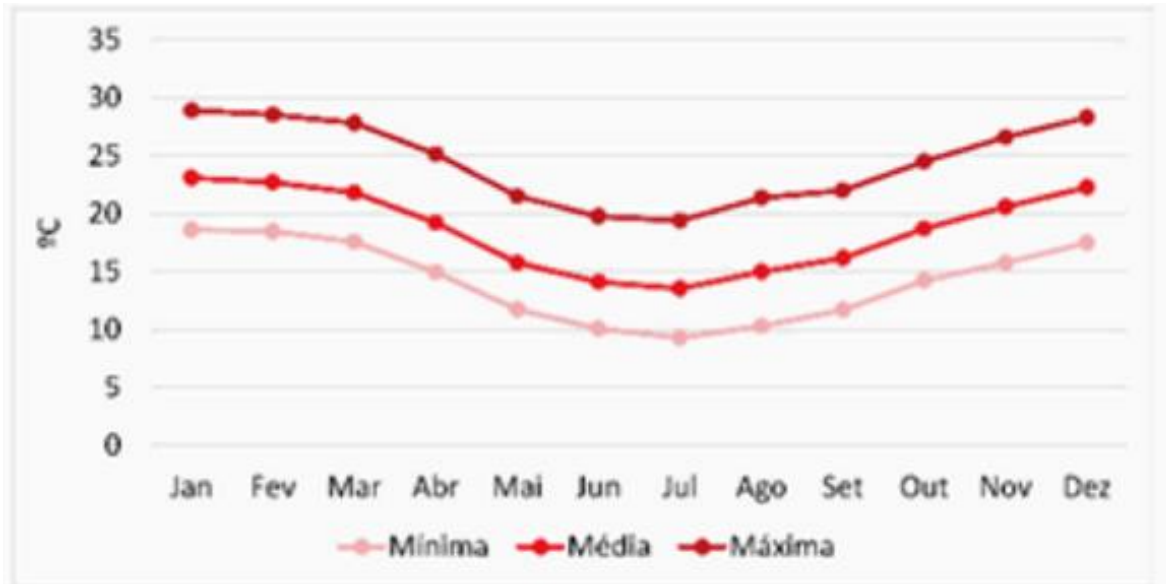
Euarda Agnolin
Fiorella Acquotta

Introduction

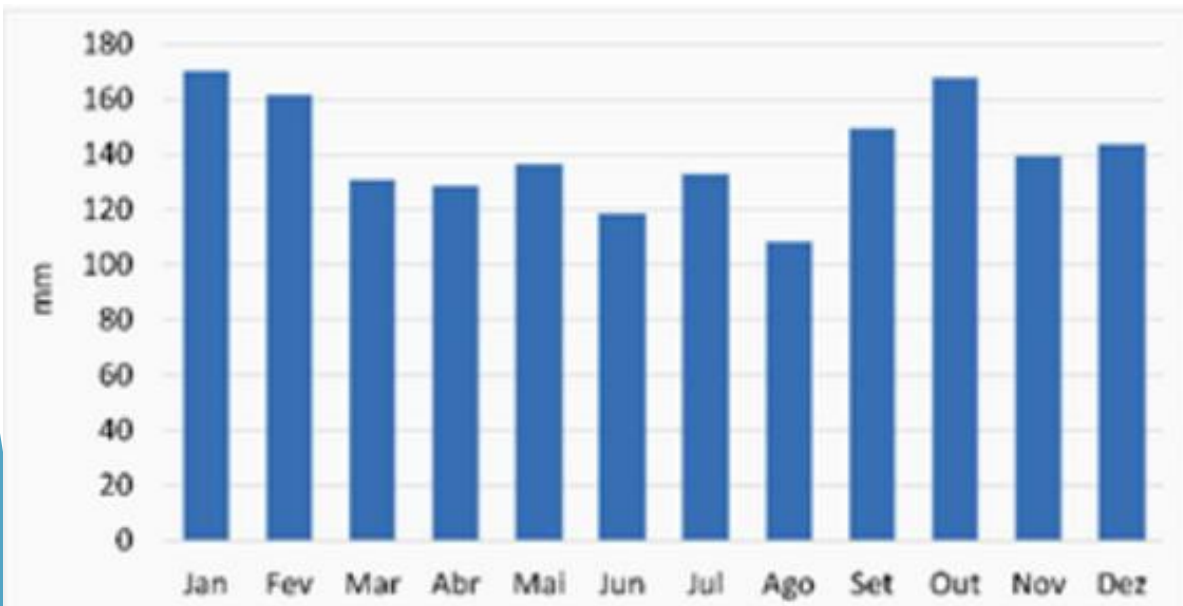
- ▶ The presence of gaps in meteorological series is a recurring problem in climate studies, potentially compromising the analysis of extreme events such as heat waves. In this context, this study aimed to evaluate different data reconstruction methodologies for filling gaps in maximum temperature series.

Location of the study area

Monthly temperature in the subtropics (1981-2010)



Monthly precipitation in the subtropical zone (1981-2010)



Map of Brazil showing Rio Grande do Sul and Santa Catarina.



World map with Brazil

Methodology

Table 01 - Weather stations used

Station	Number of failures in the series	% of failures in the series
Florianópolis	360	5,48 %
Porto Alegre	26	0,40%

Number of failures in the series per year

Years	Porto Alegre	Florianópolis
2008	6	1
2009	1	2
2010	0	0
2011	0	0
2012	0	4
2013	5	1
2014	0	0
2015	0	21
2016	5	0
2017	1	0
2018	0	0
2019	0	0
2020	0	0
2021	4	0
2022	0	0
2023	2	0
2024	0	101
2025	2	230

Methodology

Multiple Linear Regression (MLR): statistical method that models a linear relationship between a dependent variable and multiple independent variables to realize predictions.

Random Forest (RF): Machine-learned algorithm based on multiple decision factors that combines multiple results to improve accuracy and reduce overfitting.

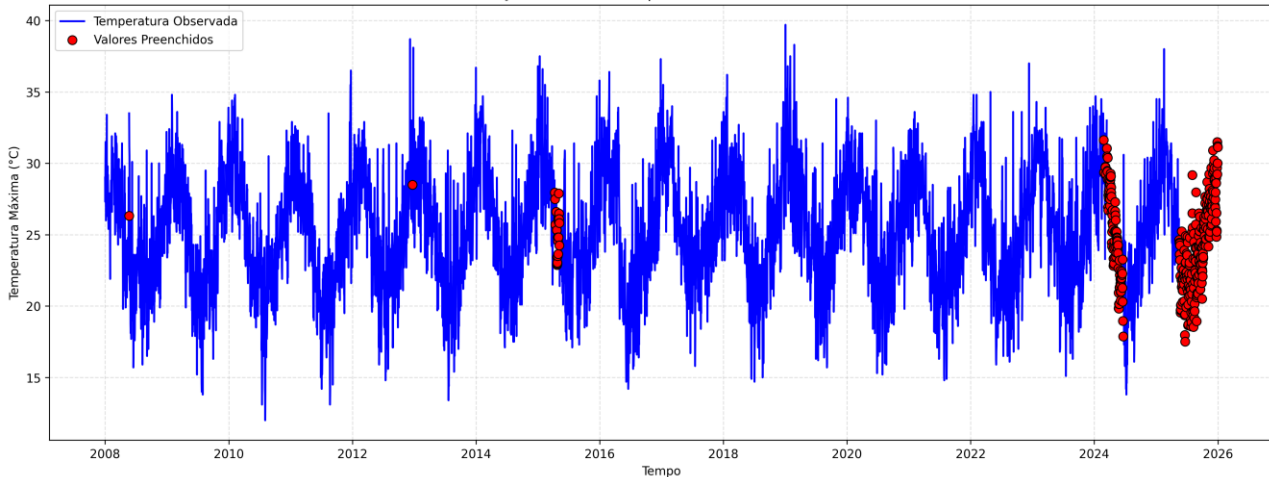
Multilayer Perceptron (MLP): type of artificial neural network composed of interconnected neuron cells capable of learning complex relationships and not linear data.

Support Vector Regression (SVR): Learned machine technique derived from support vector machines that perform regression to find a function that minimizes errors within a tolerated range.

Random Forest model

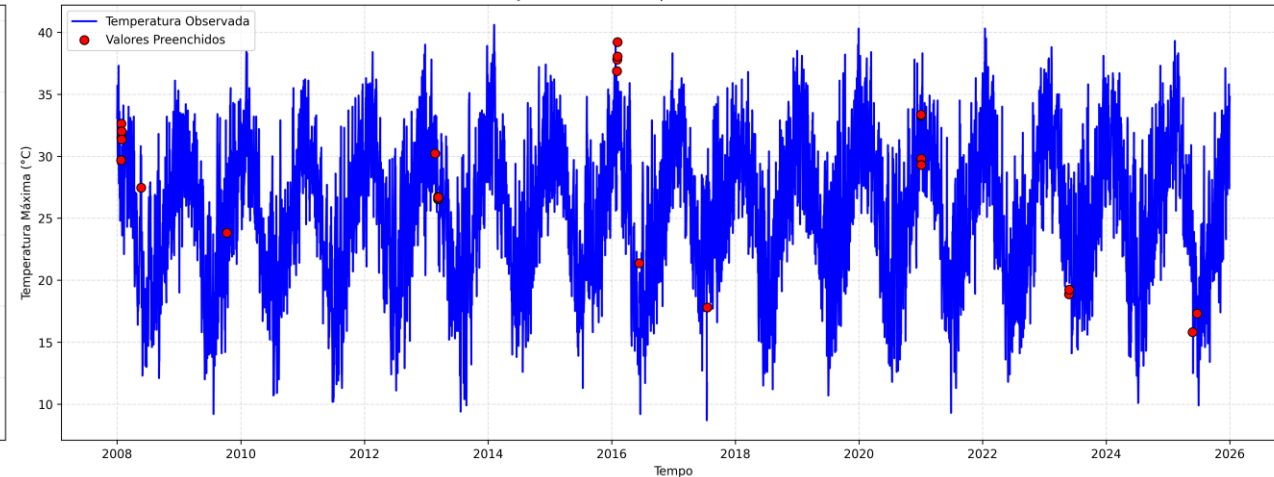
Florianópolis

Reconstrução da Série de Temperatura Máxima - Random Forest

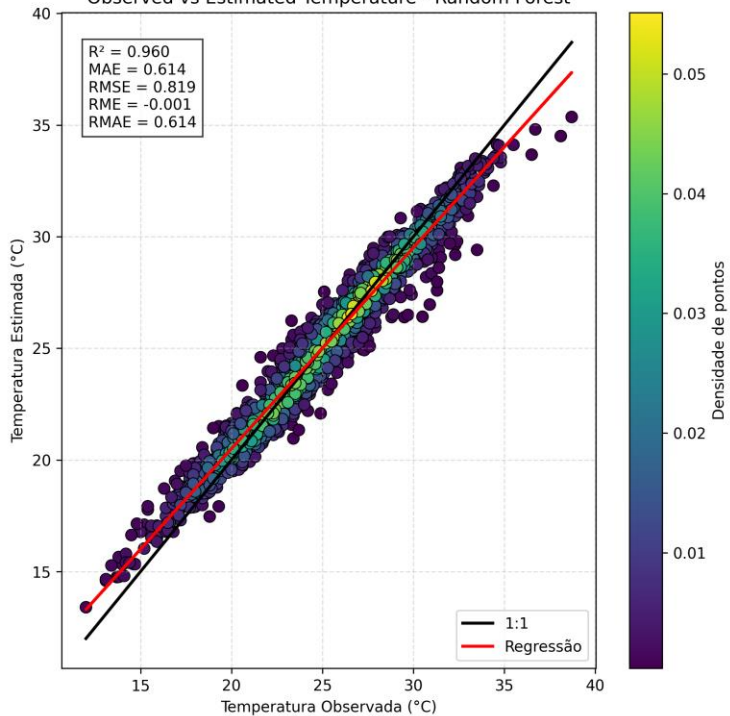


Porto Alegre

Reconstrução da Série de Temperatura Máxima - Random Forest

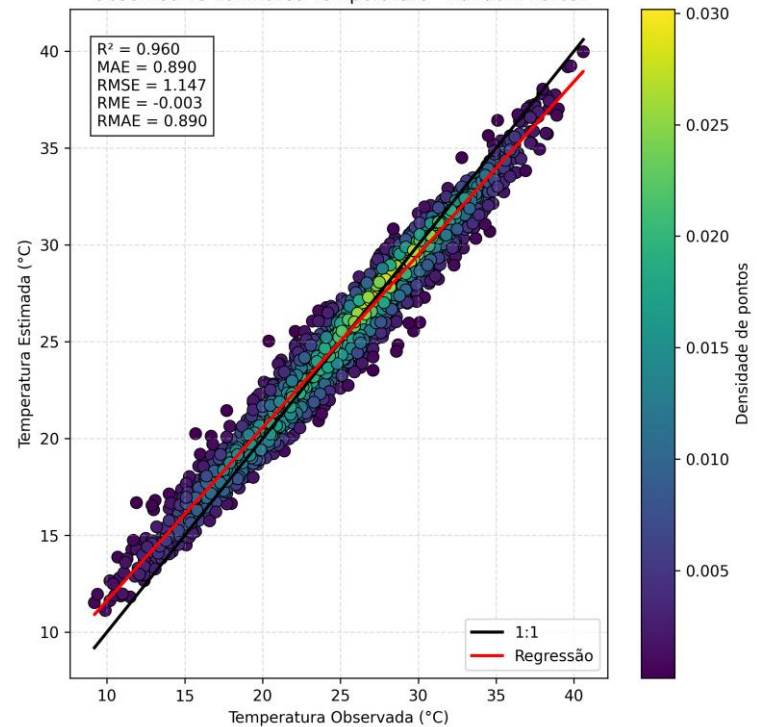


Observed vs Estimated Temperature - Random Forest



$R^2 = 0.960$
MAE = 0.614
RMSE = 0.819
RME = -0.001
RMAE = 0.614

Observed vs Estimated Temperature - Random Forest

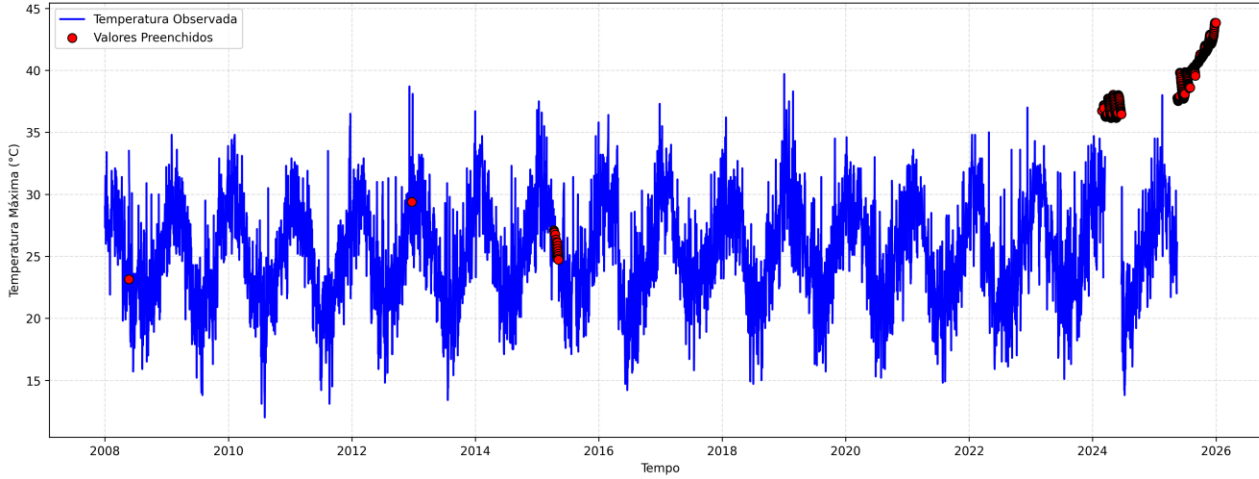


$R^2 = 0.960$
MAE = 0.890
RMSE = 1.147
RME = -0.003
RMAE = 0.890

Multilayer Perceptrons (MLP)

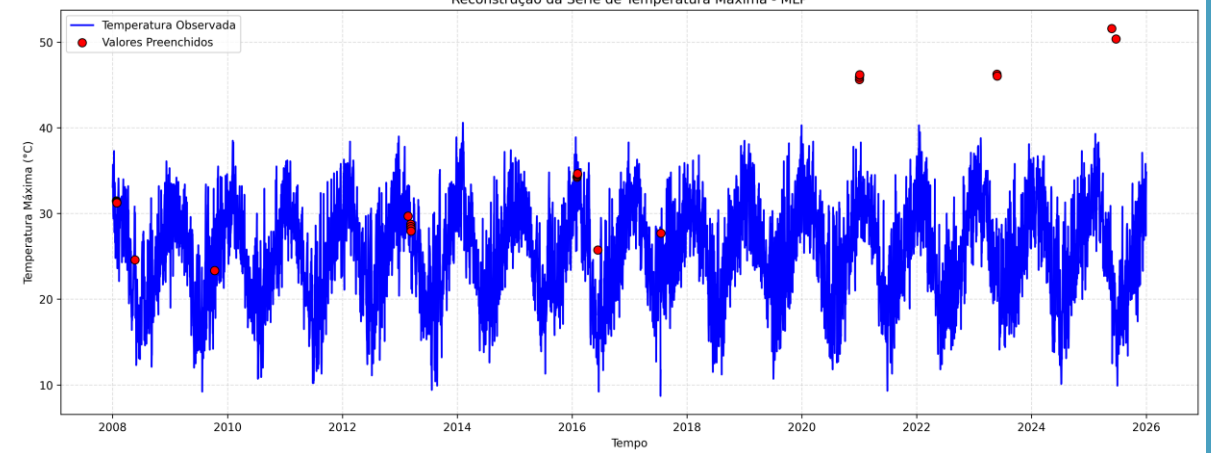
Florianópolis

Reconstrução da Série de Temperatura Máxima - MLP

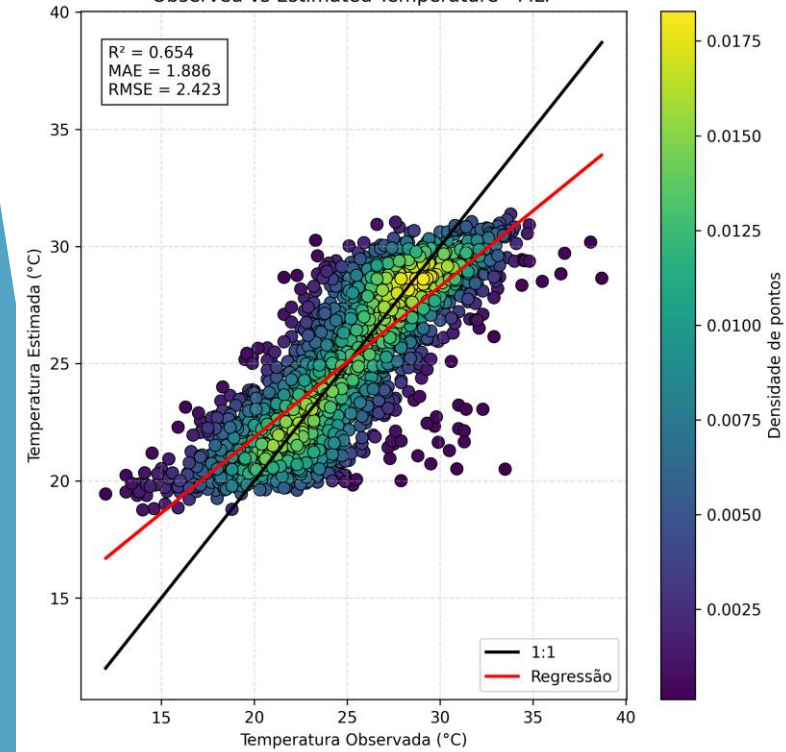


Porto Alegre

Reconstrução da Série de Temperatura Máxima - MLP

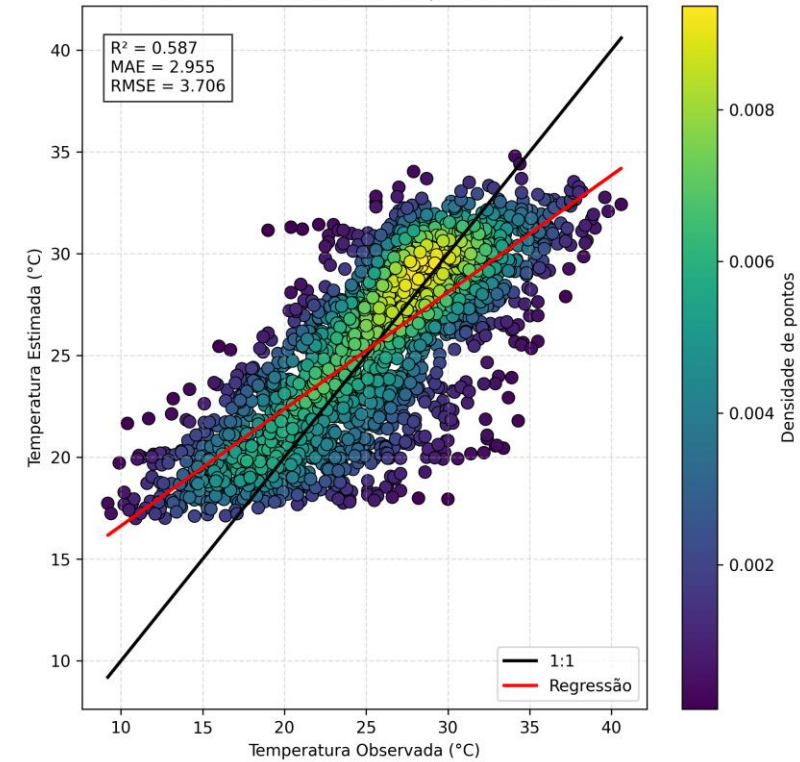


Observed vs Estimated Temperature - MLP



$R^2 = 0.654$
MAE = 1.886
RMSE = 2.423

Observed vs Estimated Temperature - MLP

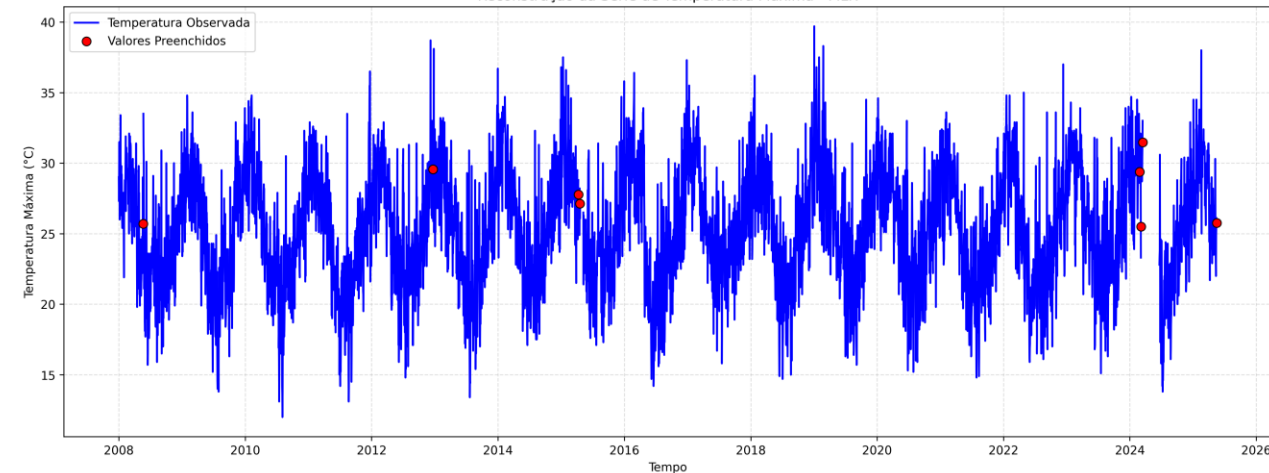


$R^2 = 0.587$
MAE = 2.955
RMSE = 3.706

MLR (Multiple Linear Regression)

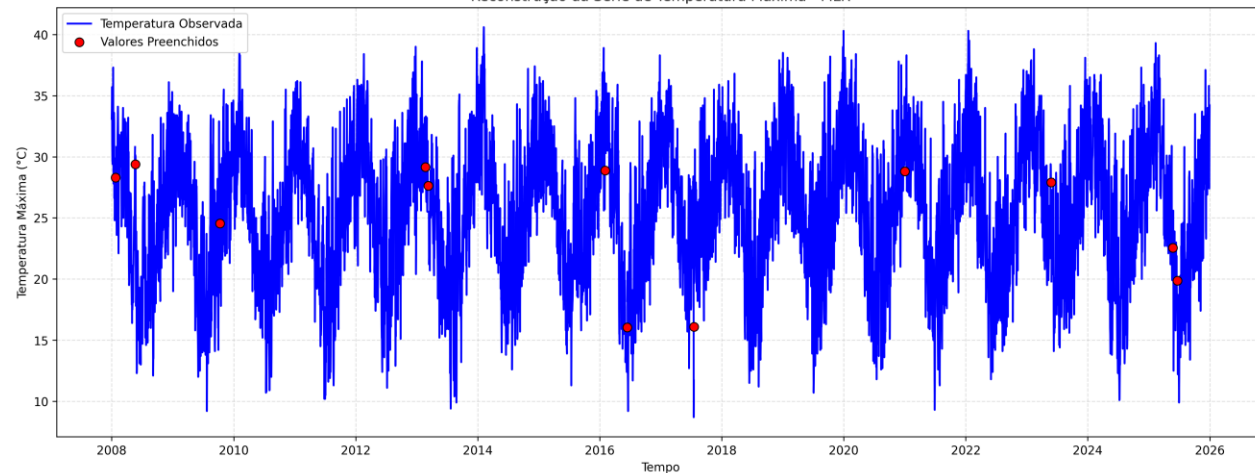
Florianópolis

Reconstrução da Série de Temperatura Máxima - MLR

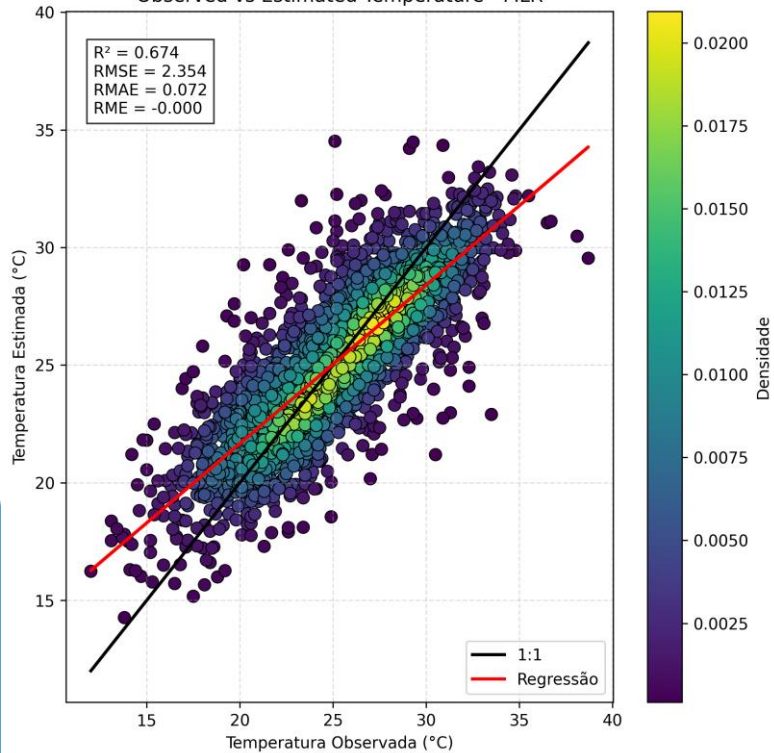


Porto Alegre

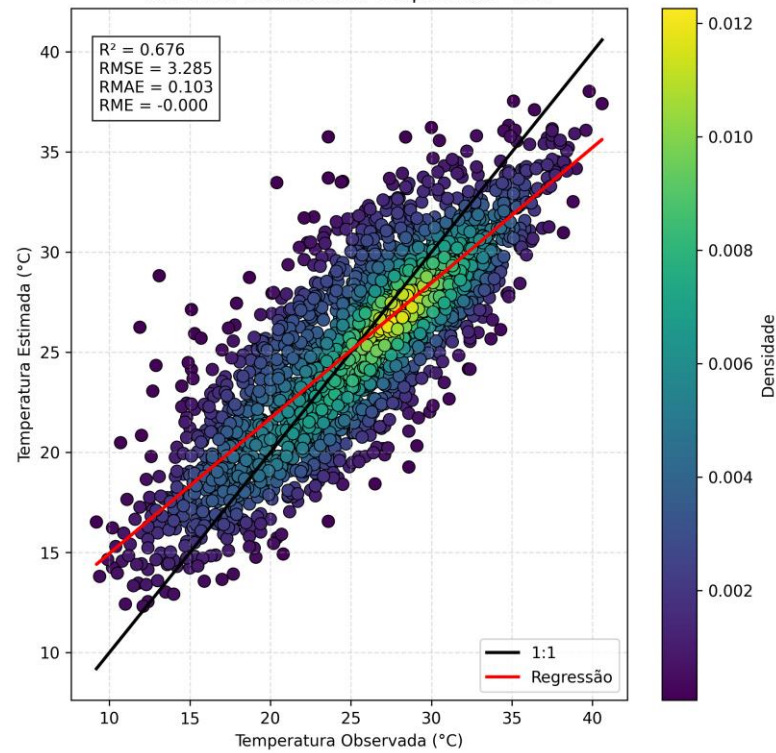
Reconstrução da Série de Temperatura Máxima - MLR



Observed vs Estimated Temperature - MLR



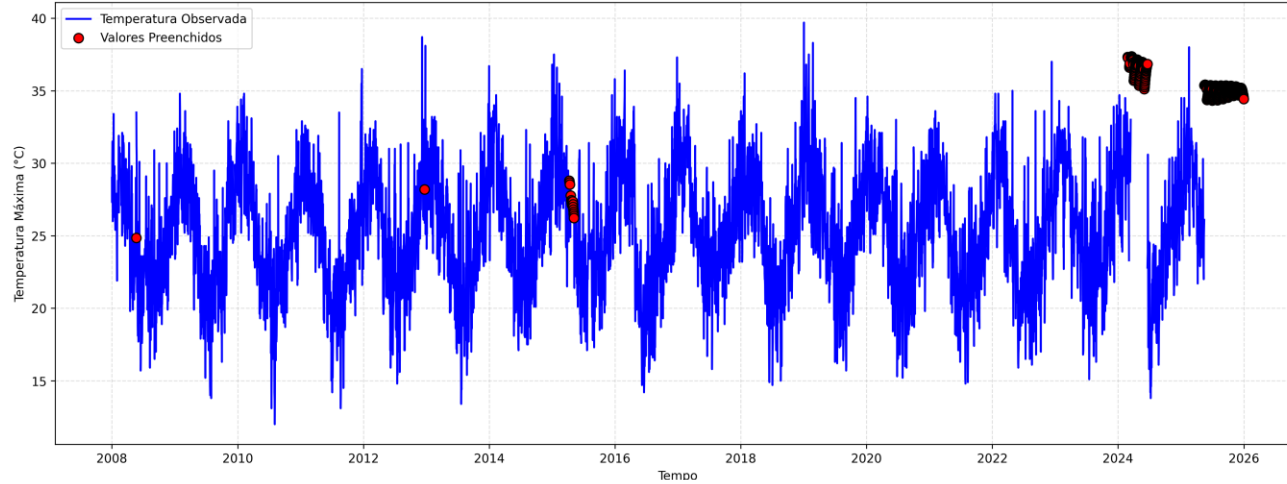
Observed vs Estimated Temperature - MLR



SVR (Support Vector Regression)

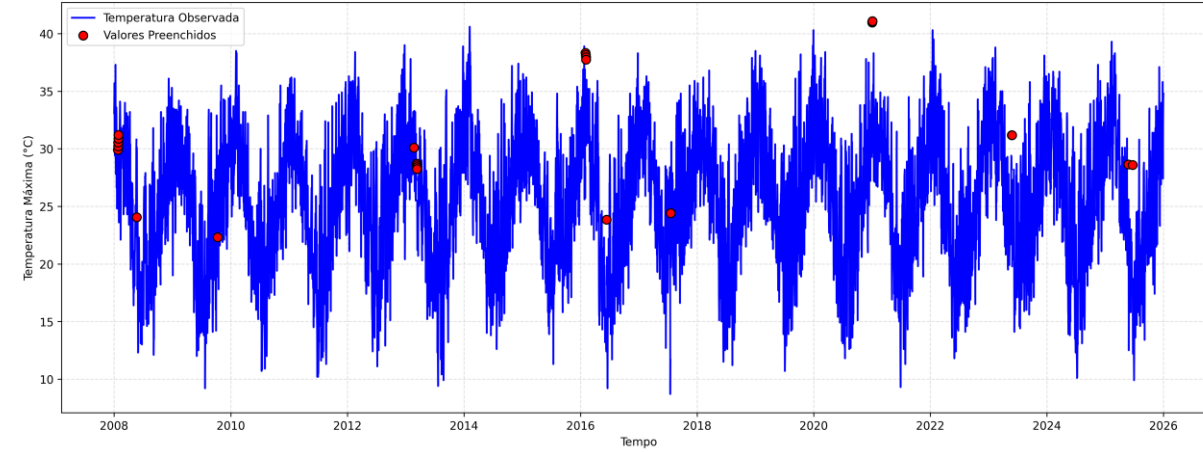
Florianópolis

Reconstrução da Série de Temperatura Máxima - SVR

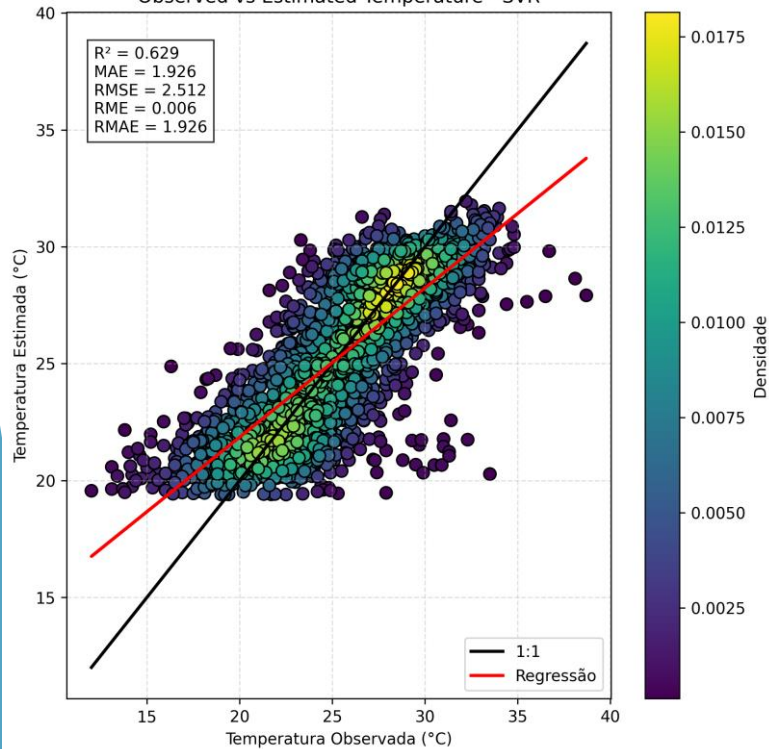


Porto Alegre

Reconstrução da Série de Temperatura Máxima - SVR

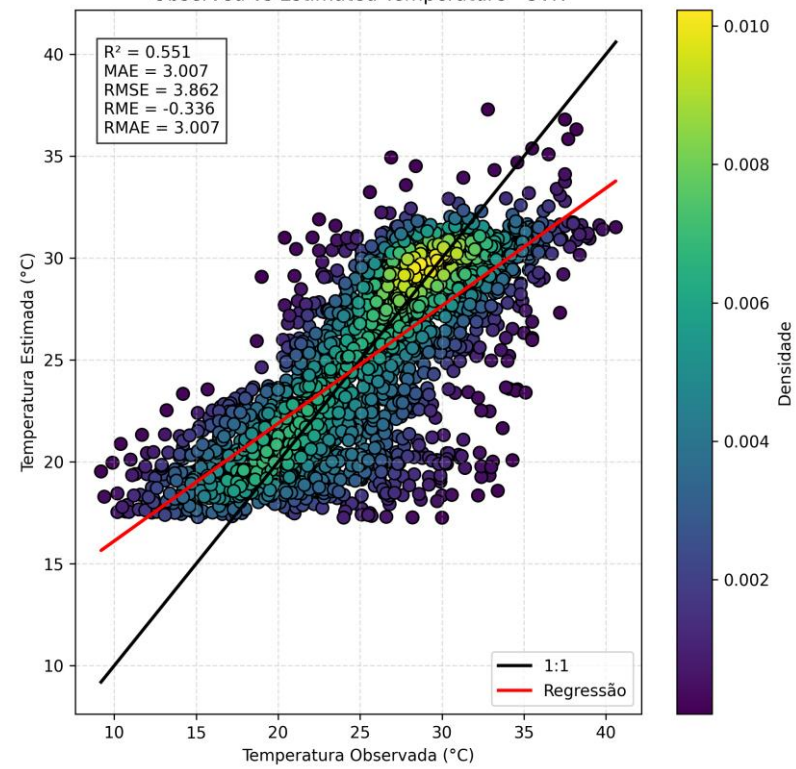


Observed vs Estimated Temperature - SVR



$R^2 = 0.629$
MAE = 1.926
RMSE = 2.512
RME = 0.006
RMAE = 1.926

Observed vs Estimated Temperature - SVR



$R^2 = 0.551$
MAE = 3.007
RMSE = 3.862
RME = -0.336
RMAE = 3.007

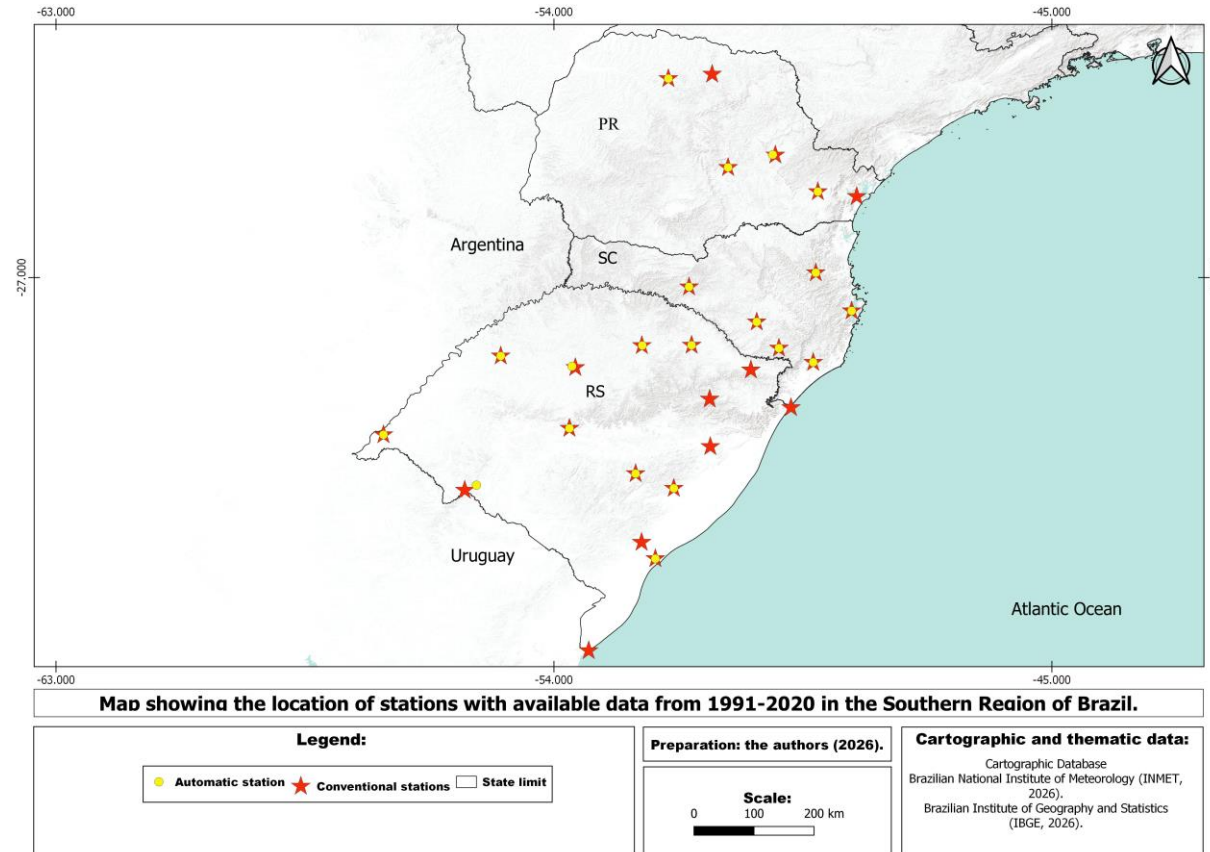
Results:

Table 02 - Model trained on the (2009 - 2014) dataset and applied to the reconstruction of the (2008 - 2025) series.

Model	Estação	R²	MAE	RMSE	RMAE	RME
MLR	Florianópolis	0.67	1.80	2.35	0.07	-1.07
	Porto Alegre	0.67	2.59	3.28	0.10	-4.62
RF	Florianópolis	0.96	0.61	0.81	0.61	-0.00
	Porto Alegre	0.96	0.88	1.14	0.88	-0.00
MLP	Florianópolis	0.65	1.88	2.42	1.88	-0.03
	Porto Alegre	0.58	2.95	3.70	2.95	-0.12
SVR	Florianópolis	0.62	1.92	2.51	1.92	0.00
	Porto Alegre	0.55	3.00	3.86	3.00	-0.33

Work in Progress

- ▶ The research will continue using the thirty stations. I will reconstruct them using Random Forest and then homogenize by Climatol. After that, I will use Climpact to perform a climate analysis of heat waves and cold spells in the subtropics from Nineteen ninety-one - two thousand twenty-five.



References

- ▶ He, M., Luo, Z., Xie, X., Wang, P., Wang, H., & Zapata-Lancaster, G. (2025). Gap filling crowdsourced air temperature data in cities using data-driven approaches. *Building and Environment*, 271, 112593.
- ▶ da Silva Junior, A. A., Gomes, R. D. S. R., De Musis, C. R., Novais, J. W. Z., Maionchi, D., & de Figueiredo, J. M. (2024). Preenchimento de falhas em séries temporais da temperatura do ar: uma comparação entre modelos de Machine Learning. *Revista Brasileira de Climatologia*, 35, 362-377.
- ▶ GUIJARRO, Jose A. Homogenization of climatic series with Climatol. **Reporte técnico State Meteorological Agency (AEMET), Balearic Islands Office, Spain, 2018.**

Thank you

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