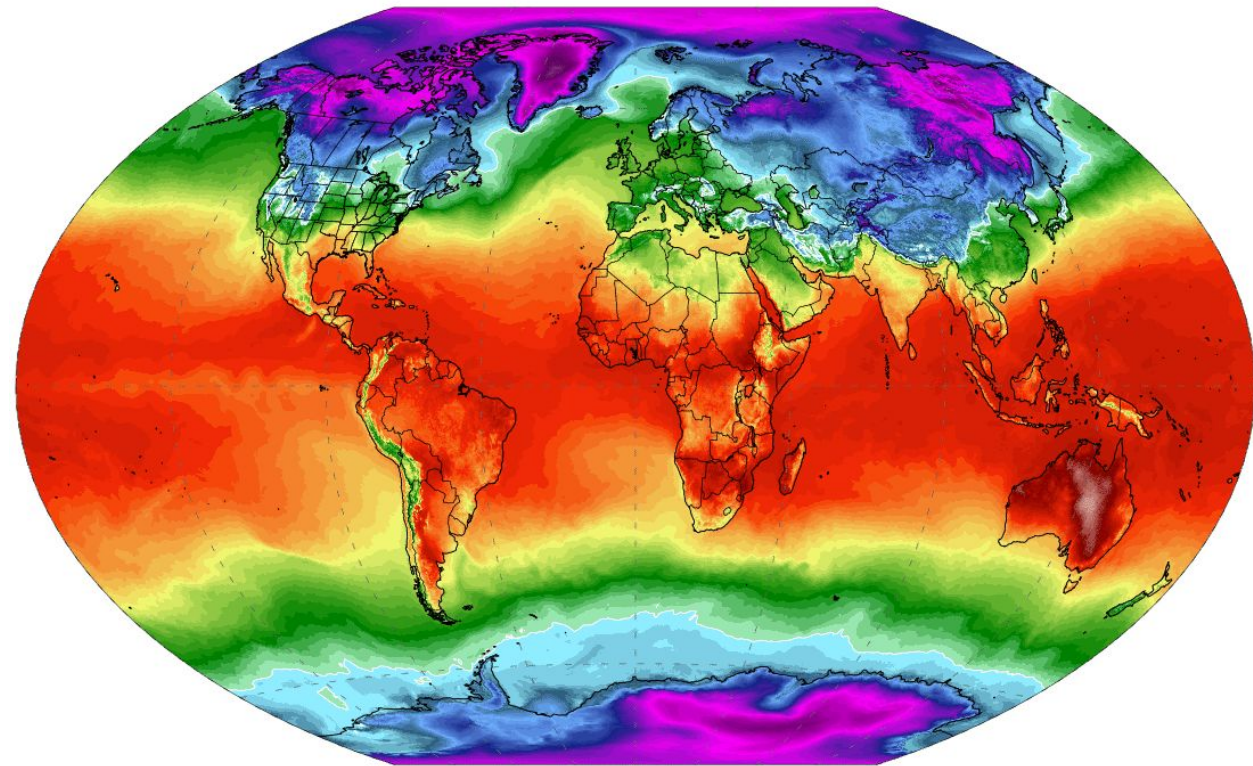


Weather prediction

GFS 2m Temperature (°C)
1-day Avg | Mon, Dec 16, 2024

ClimateReanalyzer.org
Climate Change Institute | University of Maine



Dataset

- Variables
- Only one location



Research question 1

To what extent does the Vector Autoregression improve the Linear Regression Model? Will capturing interdependencies between naturally related variables (e.g. temperature and humidity) improve modeling with VAR?

H0: Vector Autoregression does not improve the Linear Regression Model in weather prediction.

Research question 2

To what extent are periodic variables that follow seasonal patterns more predictable than variables that don't exhibit these tendencies?

H0: Variables exhibiting seasonal periodicity do not have statistically lower forecasting errors than variables without such patterns.



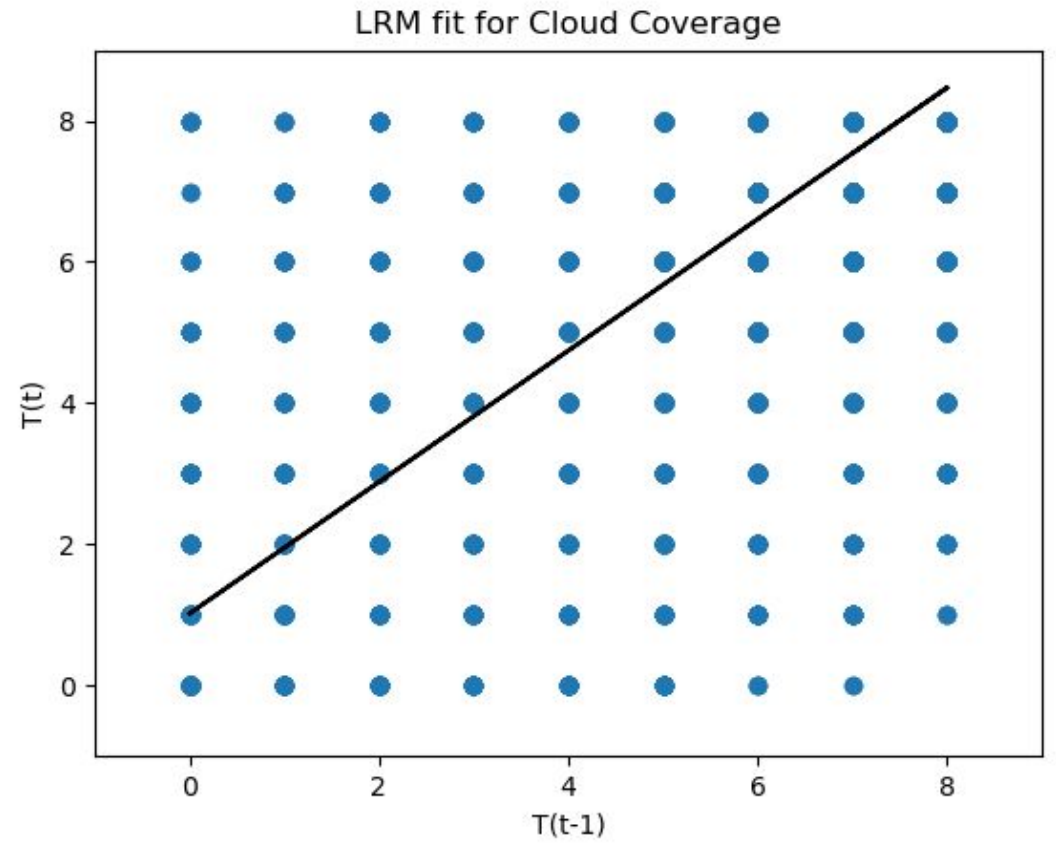
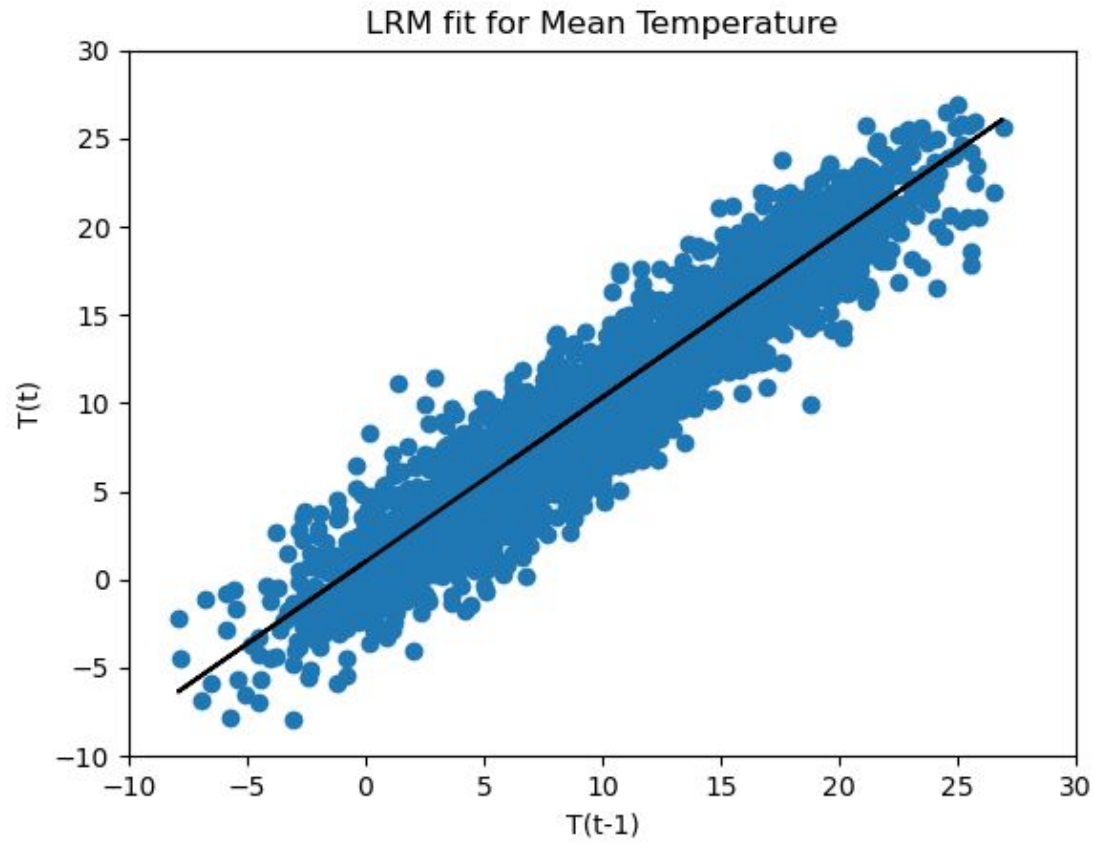
Research question 3

What is the effect of sample size on predicting power with a Vector Autoregression in weather prediction?

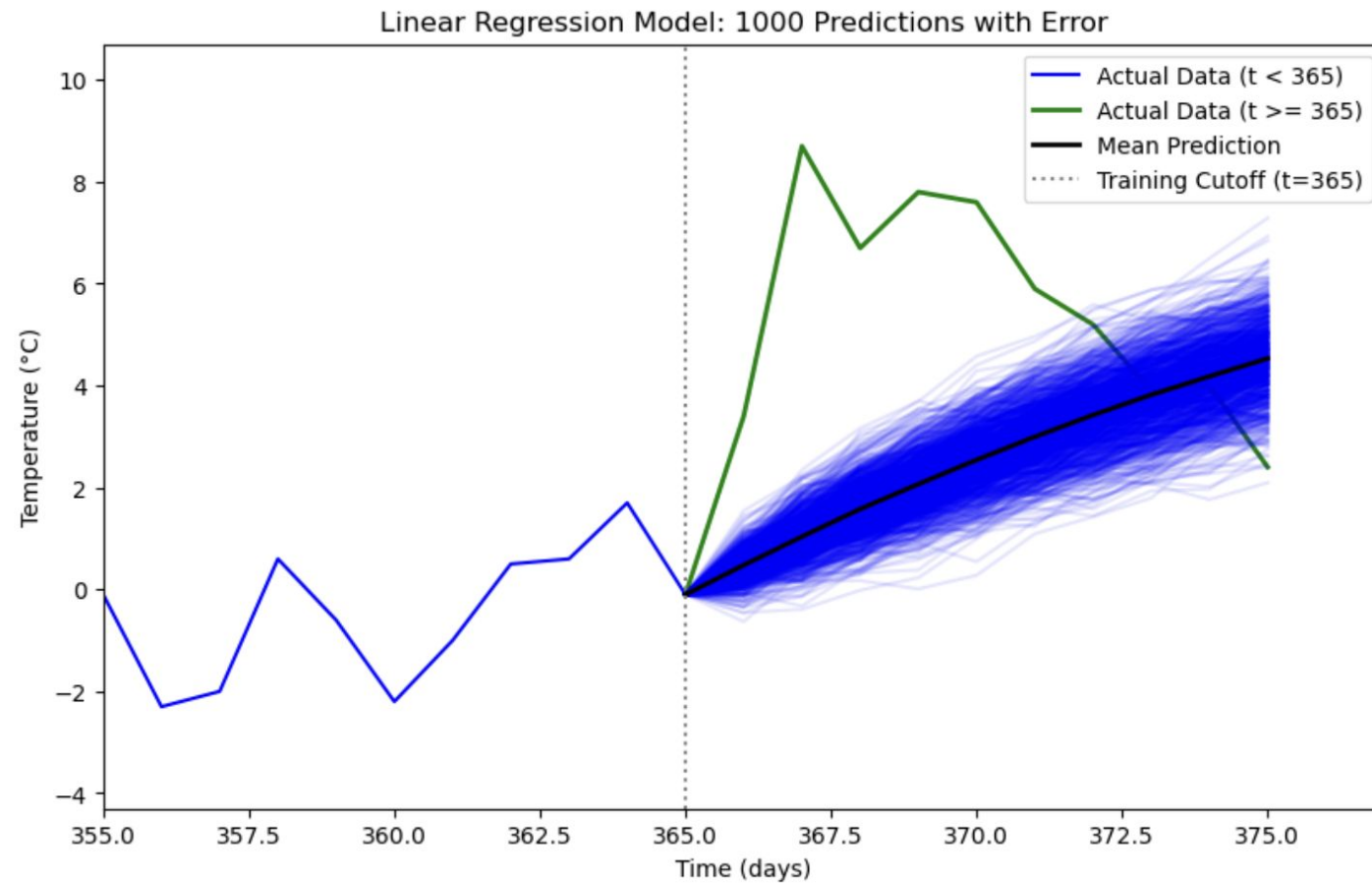
H0: Increasing the sample size does not have an effect on the predicting power of a Vector Autoregression.



LRM fit



LRM prediction

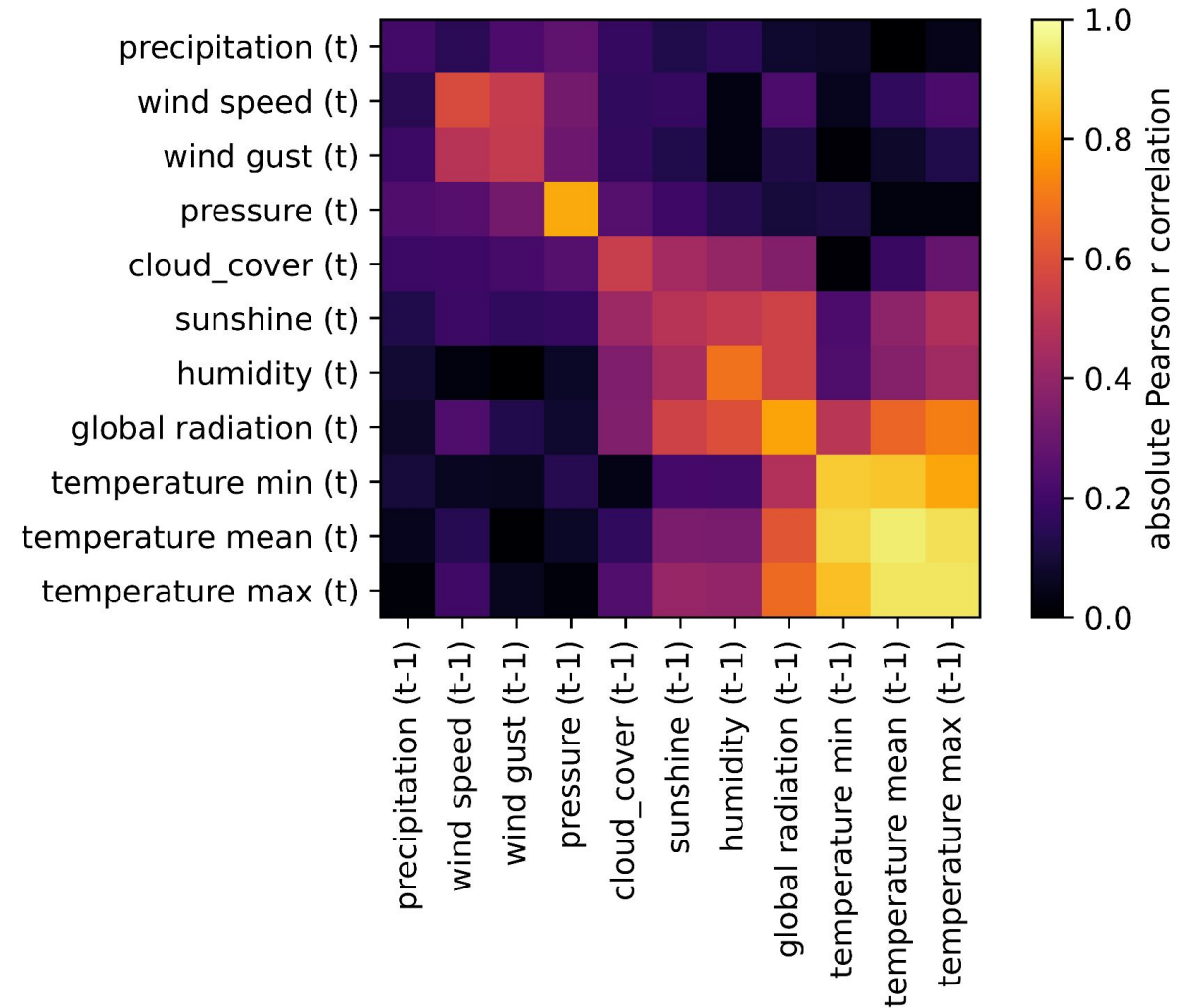


VAR explanation

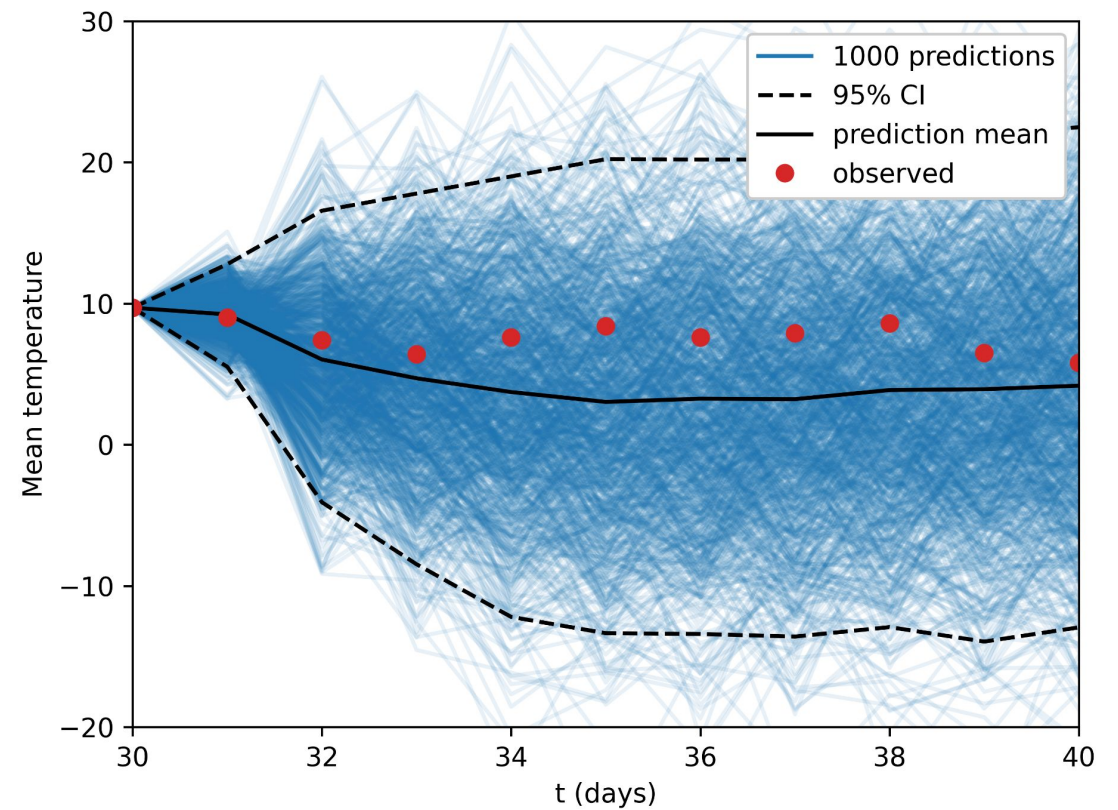
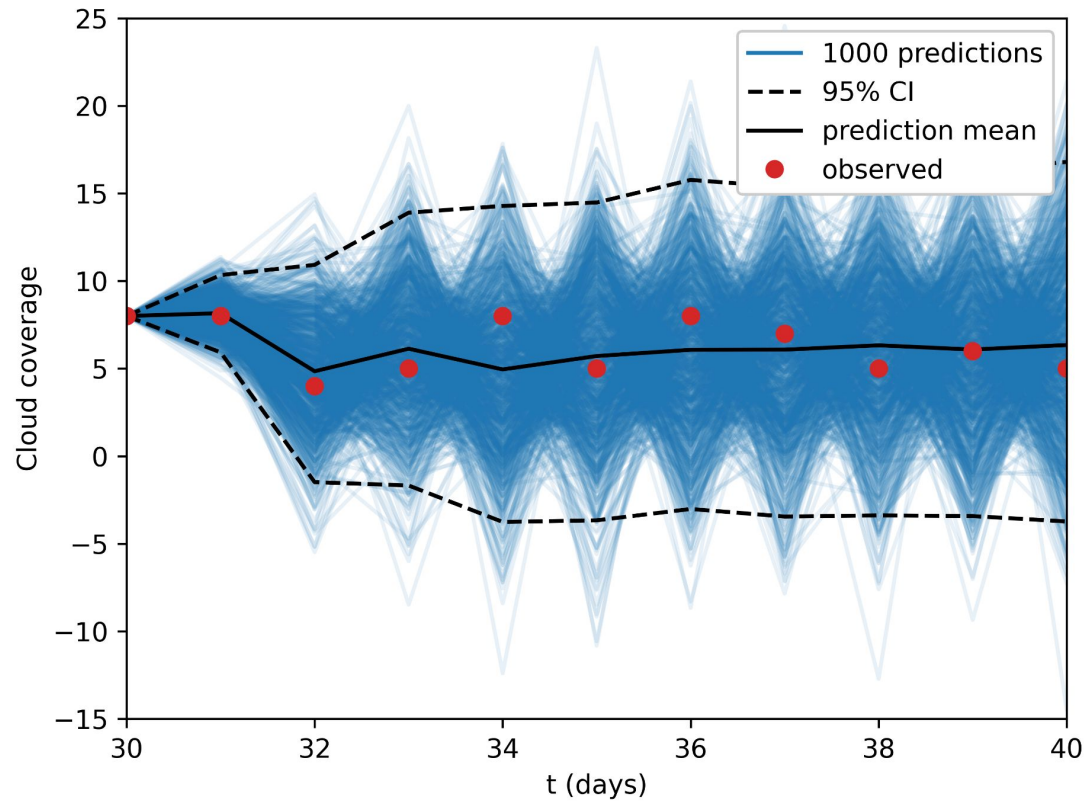
$$\vec{y}(t) = \vec{c} + M\vec{y}(t-1) + \vec{e}$$

$$Y_t = C + M \cdot Y_{t-1}$$

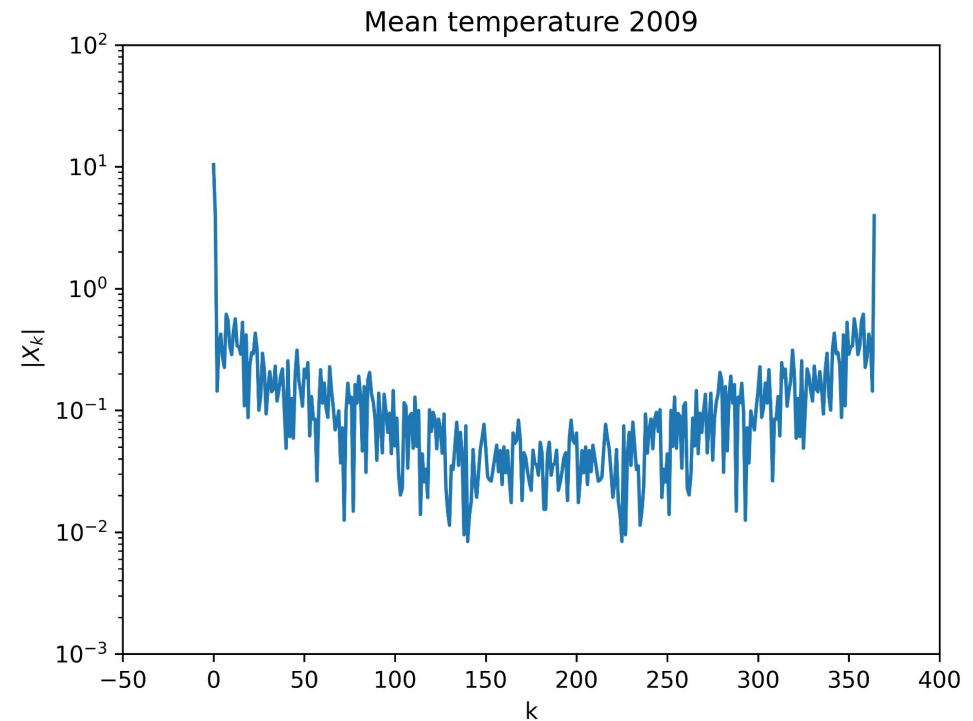
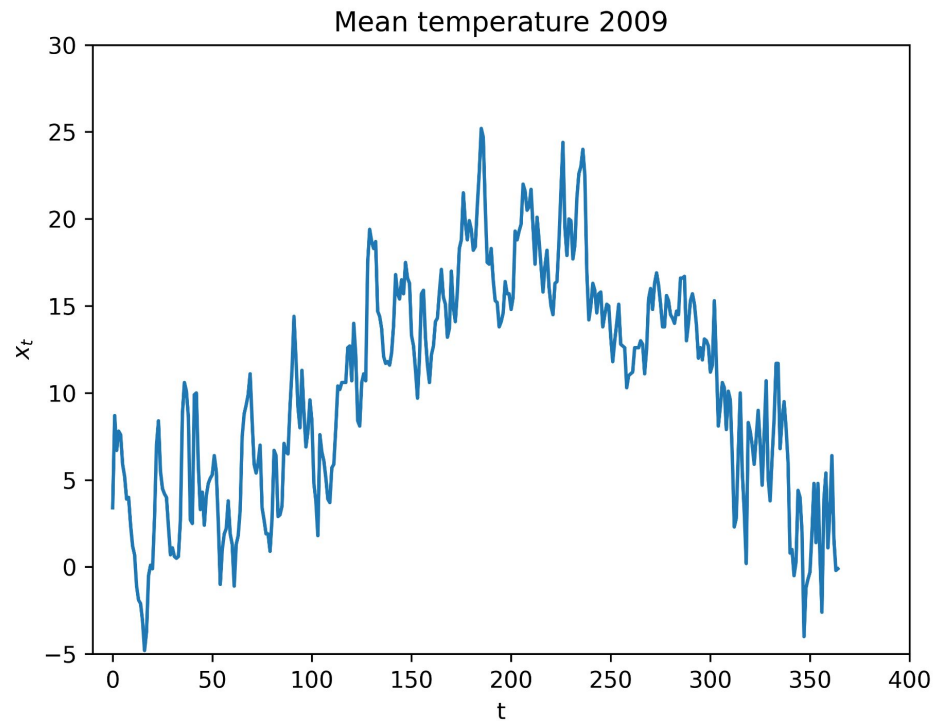
$$\text{residuals} = Y_t - (C + M \cdot Y_{t-1})$$



VAR predictions (alternative)



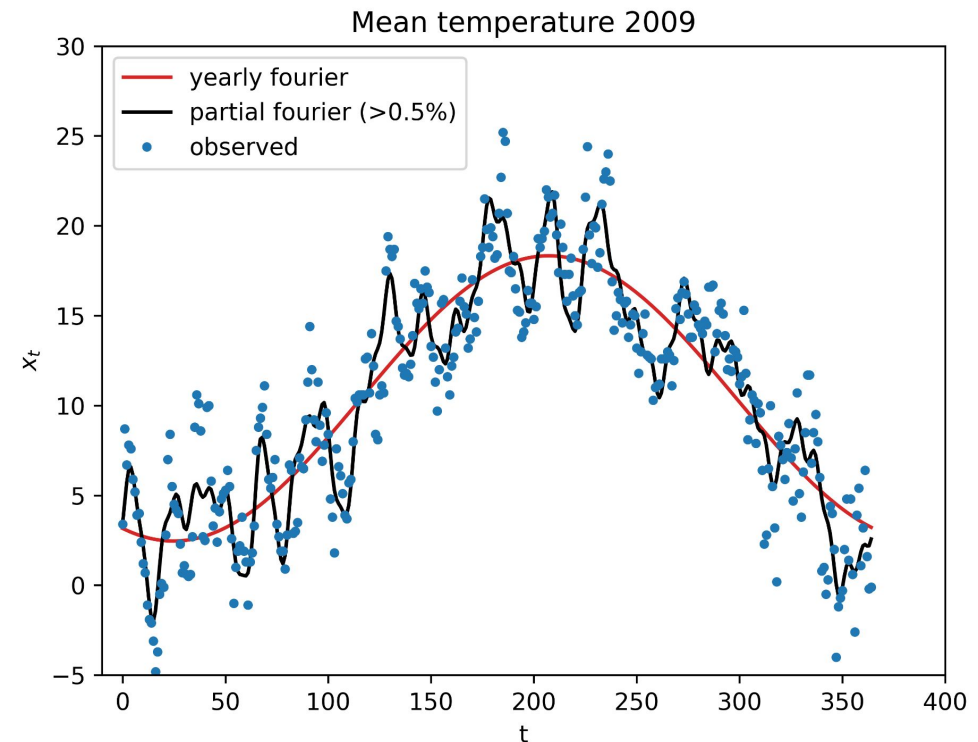
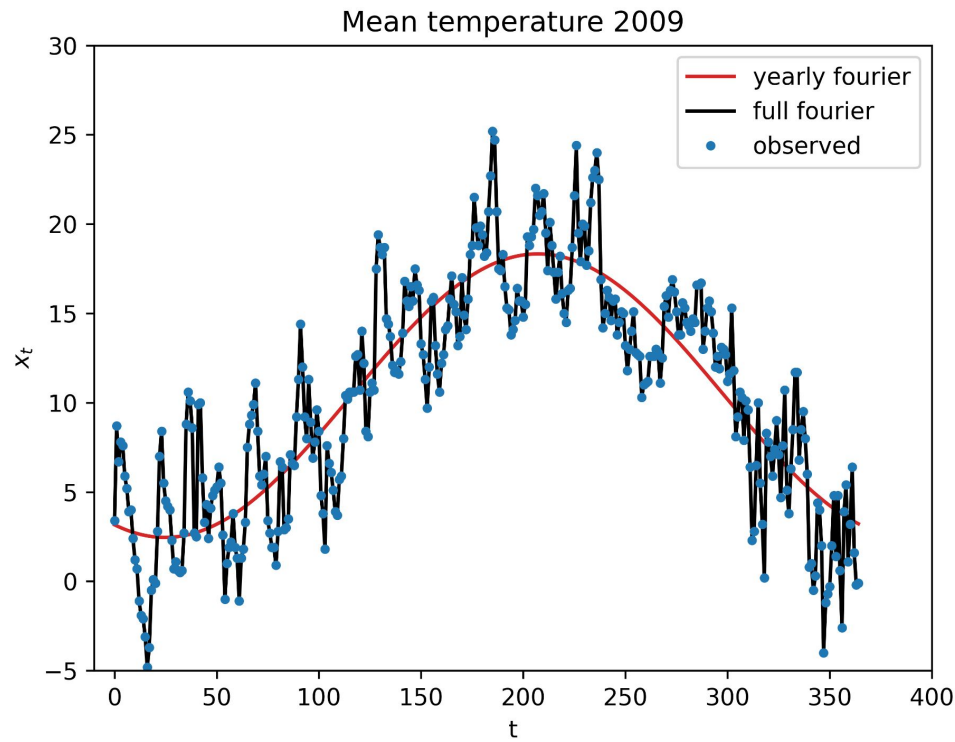
Discrete fourier transform:
$$X_k = \sum_{t=0}^{N-1} x_t \cdot e^{\frac{-i2\pi kt}{N}}$$



Reconstruction:

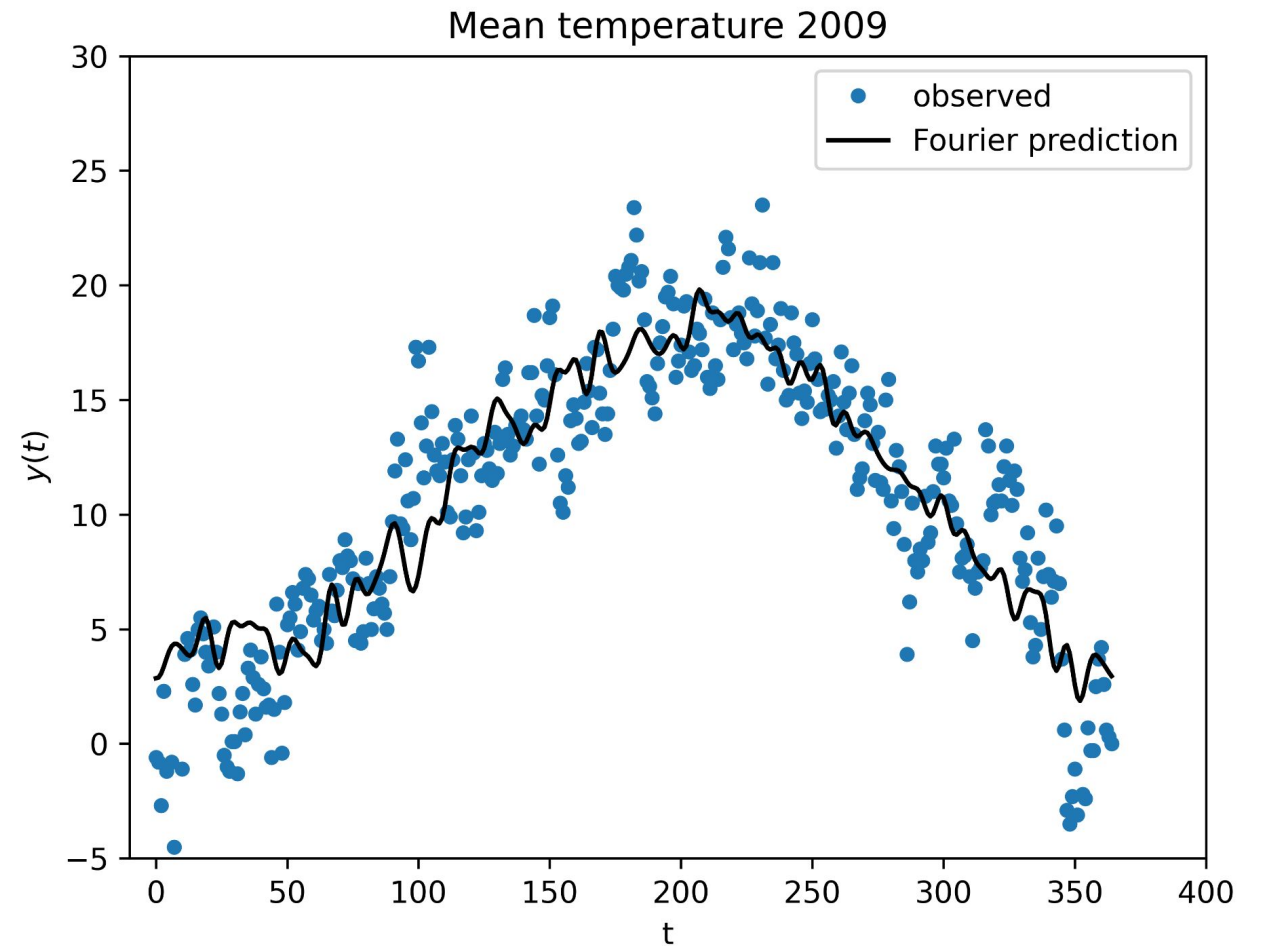
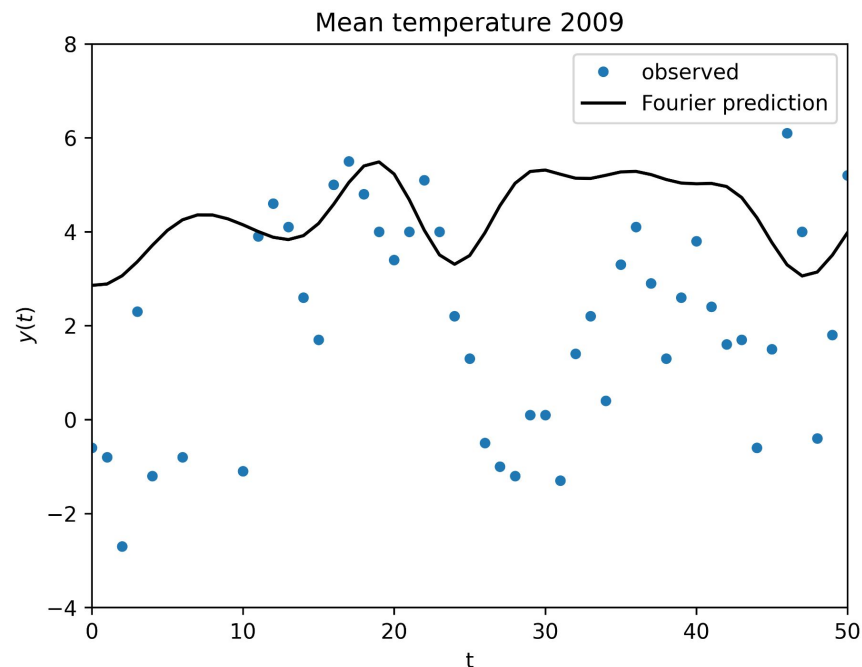
$$x_t = \sum_{k=0}^{N-1} A_k \cos\left(\frac{-i2\pi kt}{N} + \delta_k\right)$$

$$A_k = |X_k| \quad \delta_k = \arg(X_k)$$

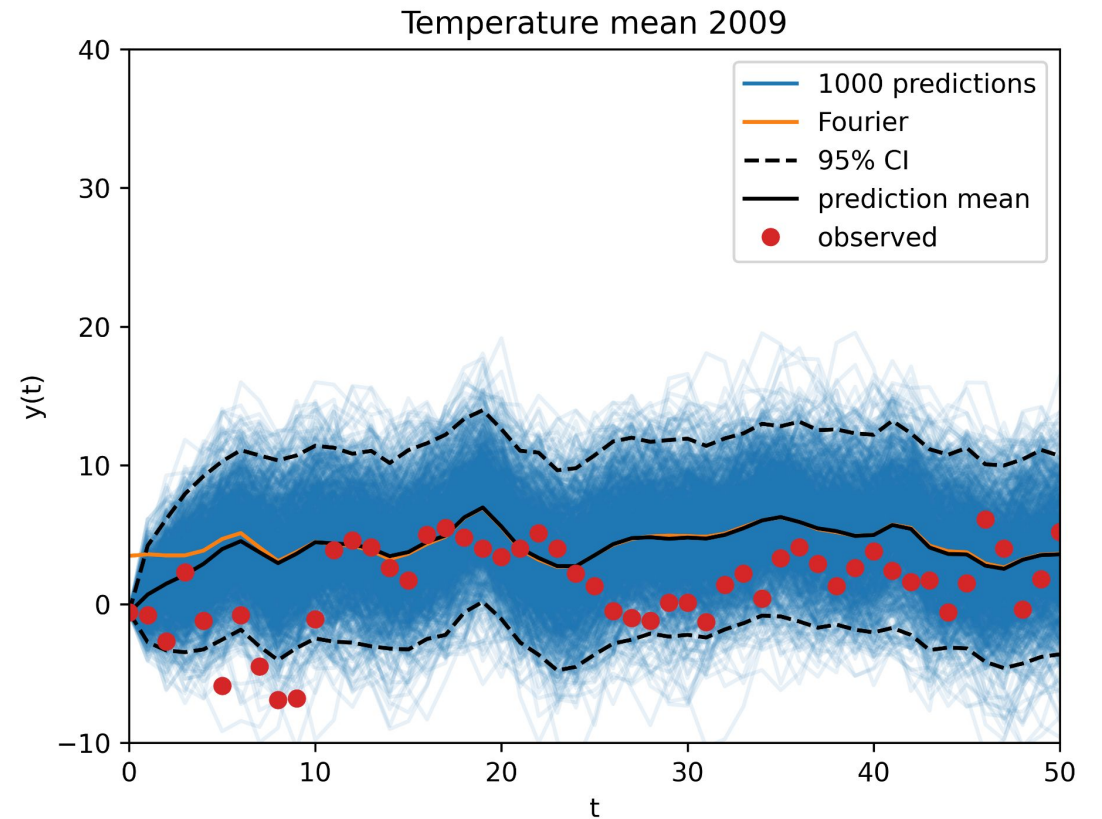
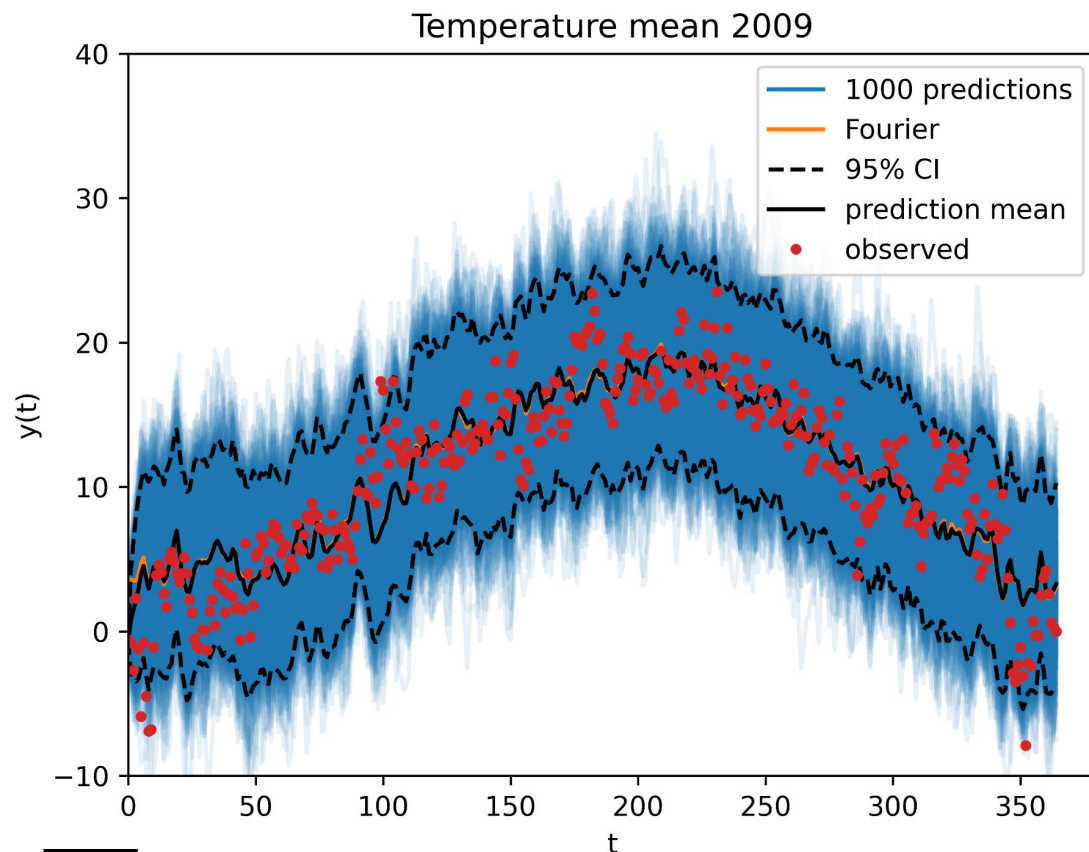


Fourier prediction

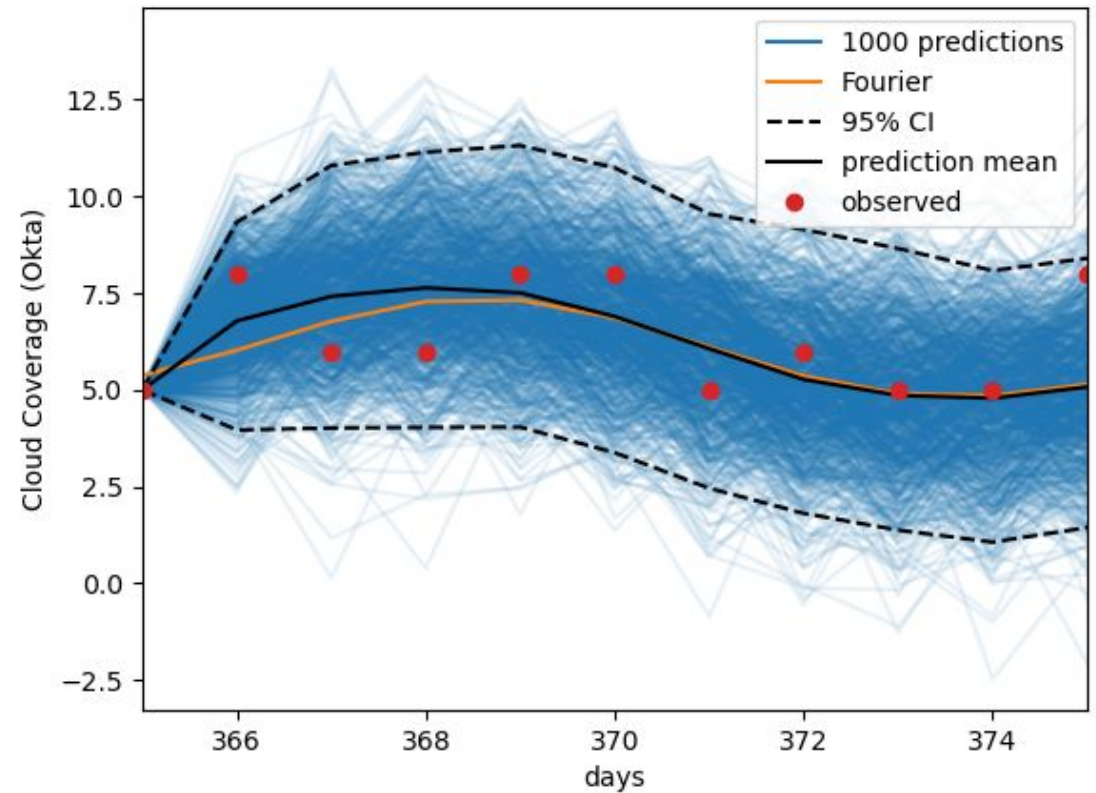
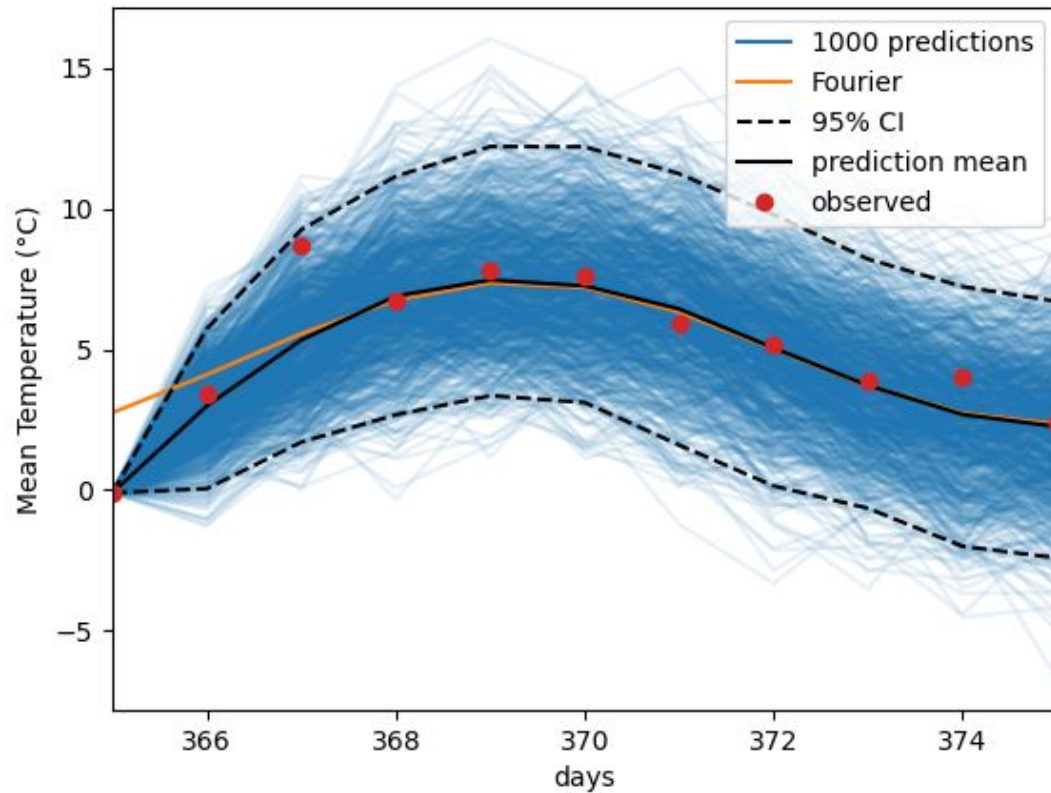
$$y(t) = F(t)$$



Hybrid prediction: $\vec{y}(t) = \vec{F}(t) + M \cdot (\vec{y}(t-1) - \vec{F}(t)) + \vec{e}(t)$



Hybrid (lucky) prediction



Question 1 Results:

H0 : Vector Autoregression does not improve the Linear Regression Model in weather prediction. (Reject)

Diebold-Mariano test

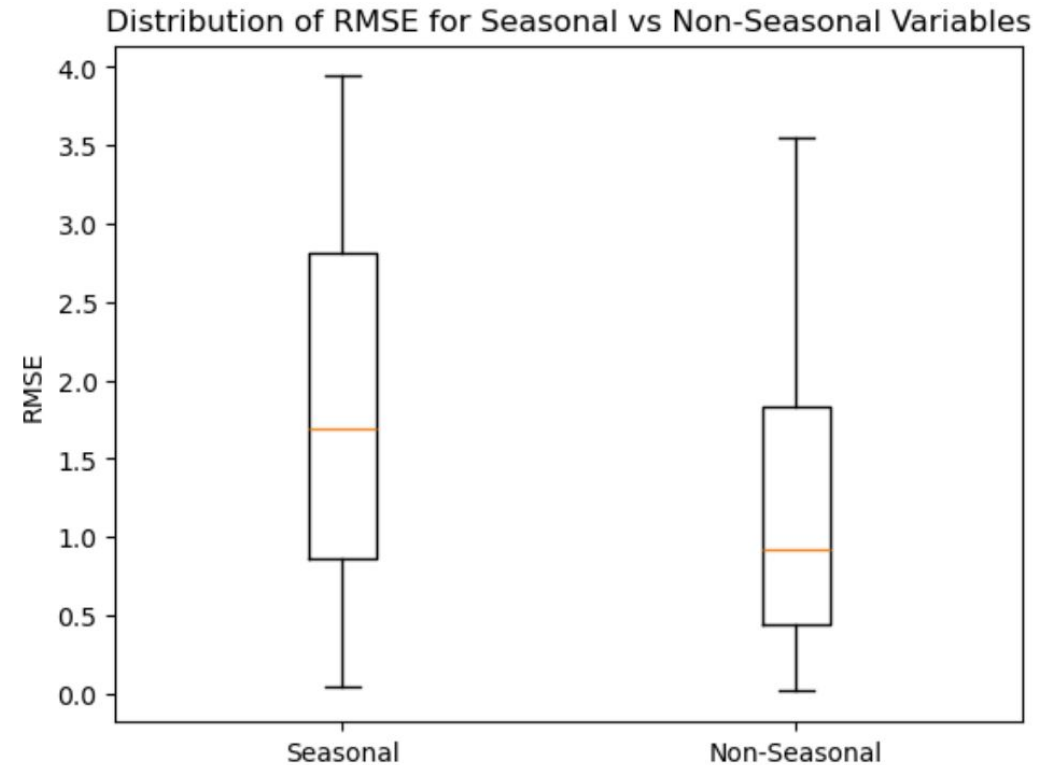
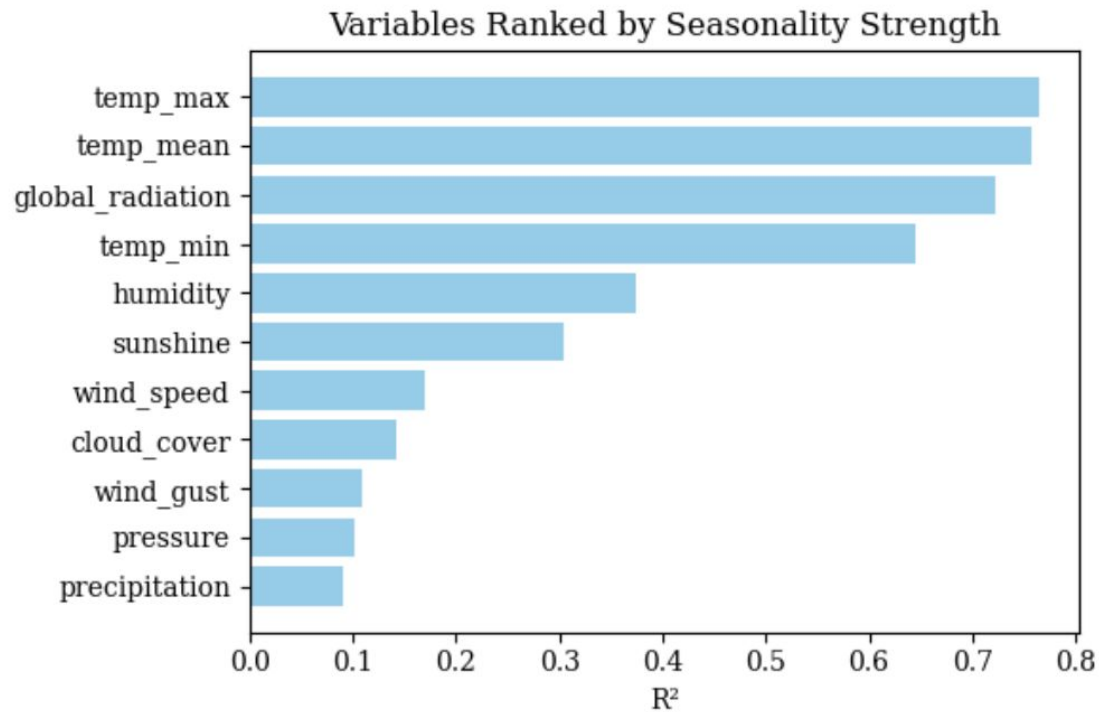
Variable	DM_stat	p_value	R^2 > 0.85	highly correlated r > 0.5
cloud_cover	0.843585	0.398902		x
wind_speed	1.733281	0.083046		x
wind_gust	0.881572	0.378008		
humidity	3.114168	0.001845		x
pressure	-2.239301	0.025136	x	
global_radiation	4.665723	0.000003		x
precipitation	1.354706	0.175511		
sunshine	2.621137	0.008764		
temp_mean	-2.450796	0.014254	x	
temp_min	-1.376901	0.168543	x	x
temp_max	-1.293419	0.195866	x	x



Question 2 Results

H0: Seasonality does not make a variable more predictable in the VAR framework (in terms of lower RMSE). (Accept)

Two Sample t-test



Question 3 Results

H0: Increasing the sample size does not have an effect on the predicting power of a Vector Autoregression. (Reject)

Sample Size	Aggregated MSE	1
50	0.900 0.895	
100	0.865 0.863	
150	0.841 0.842	
200	0.815 0.815	
250	0.800 0.797	
300	0.781 0.780	
350	0.763 0.763	
400	0.750 0.750	

Pearson Correlation: -0.992

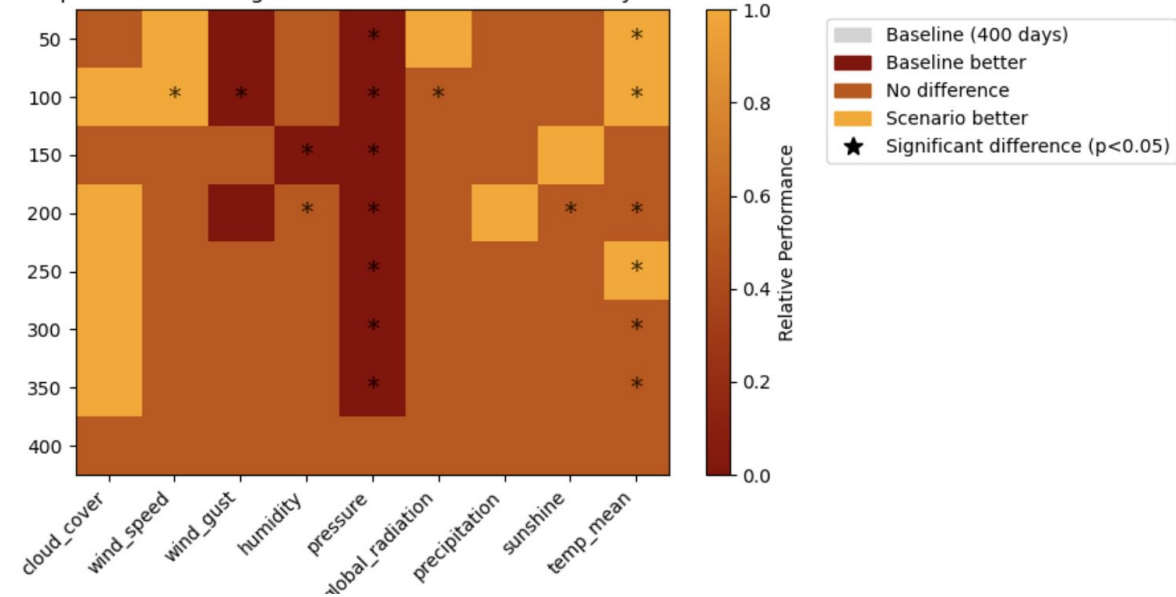
p-value: 0.000

Significance: Significant ($p < 0.05$)

Conclusion: Reject H_0

Diebold-Mariano test

Comparison of Training Window Performance vs 400-day Baseline



1. Please disregard the results of the Aggregate MSE. They are not statistically correct and should not have been included in the presentation.

Conclusion

- Weather Prediction is Hard!
- Var models do not provide consistent efficiency over standalone linear models, if that variable follows a strong linear trend.



Questions

