

# Konnichiwa!

Welcome to My Forecasting Project on  
Temperature & Salinity

# Understanding the Future: Temperature & Salinity Forecasting

Why predicting  
temperature & salinity is  
important

climate monitoring

marine life impact



# The Data That Drives Our Predictions

IHI

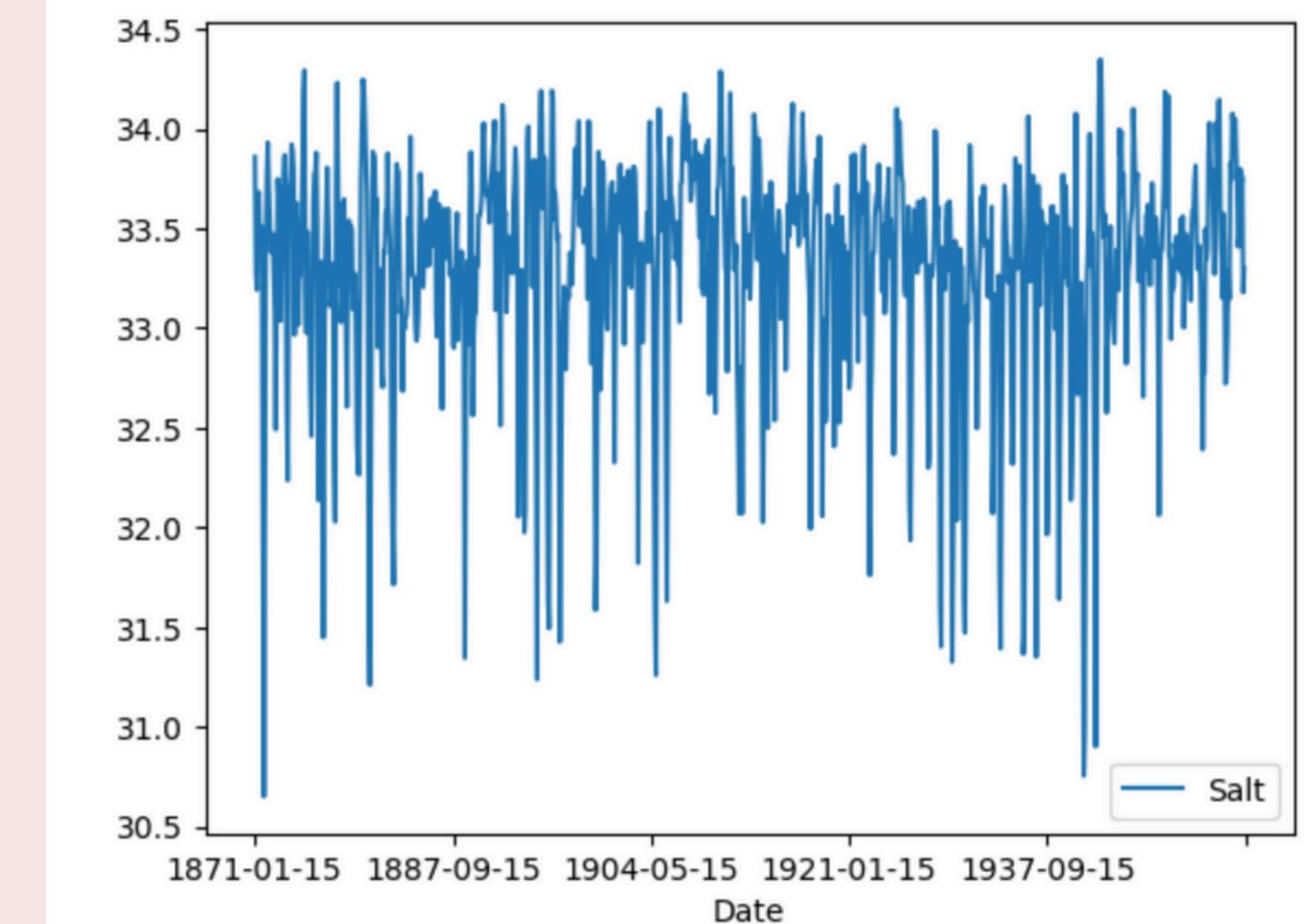
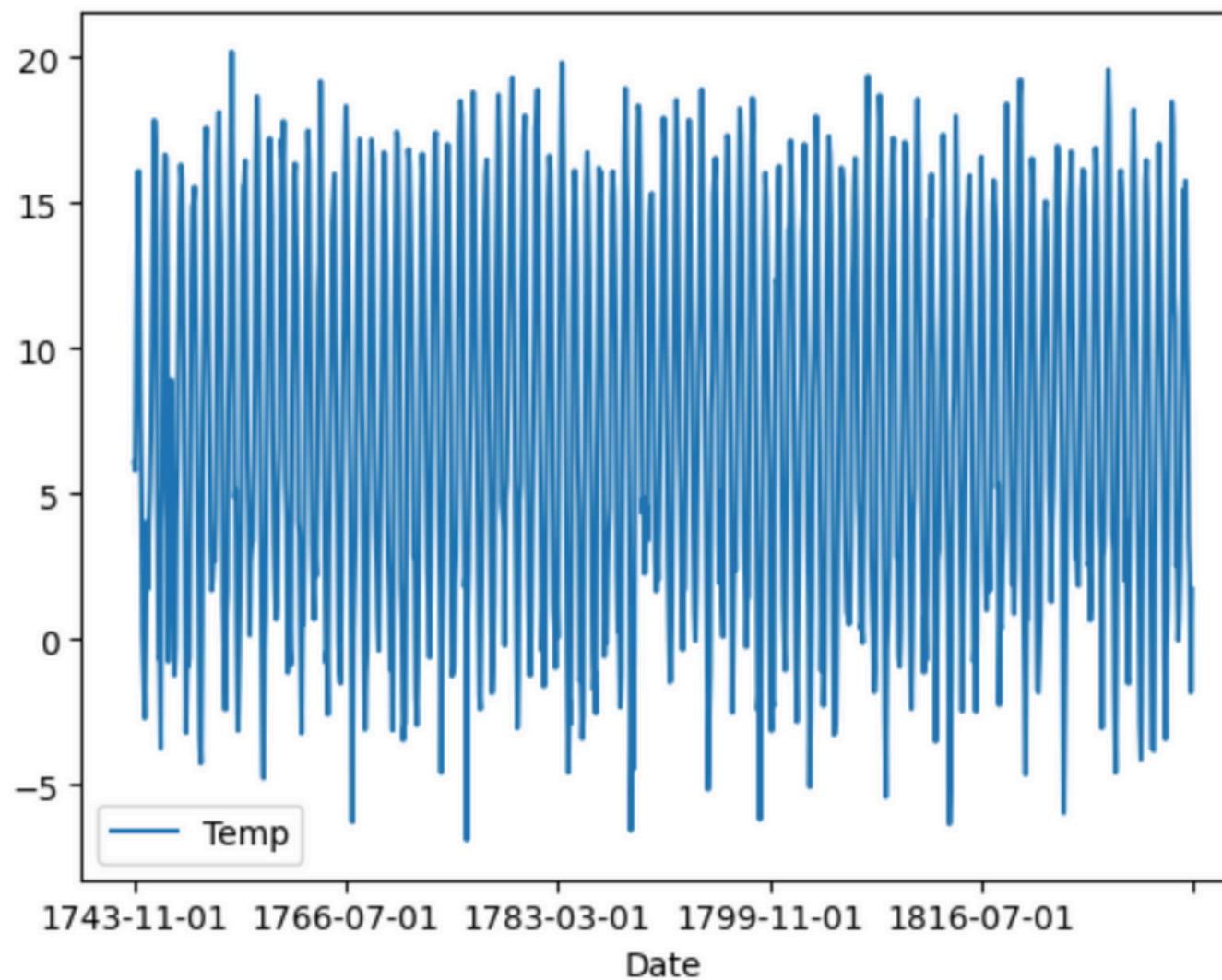
Dataset contains 1000 rows with historical temperature and salinity values.

1743-1833

Temperature

Salinity

1871-1954



# Choosing the Right Approach

## Linear Regression

Basic benchmark model

## Random Forest

Captures non-linearity well.

## SARIMA:

Used for time-series trends & seasonality.

Model	Pros	Cons
Linear Regression	- Simple and interpretable.- Fast computation.	- Assumes a linear relationship, which may not hold for complex patterns.- Less accurate for non-linear time series.
Random Forest	- Captures non-linearity.- High accuracy with low MAE & RMSE.- Robust to overfitting with enough trees.	- Computationally expensive.- Less interpretable compared to linear models.
SARIMA	- Good for capturing seasonality and trends.- Works well for time series forecasting.	- High computation time.- Requires extensive parameter tuning.- Poor performance if data is highly irregular.

# SARIMA approach

```
import libraries  
-numpy  
-pandas  
-matplotlib
```

Load CSV file  
set Date as index

H0--> non stationary  
H1--> stationary

Plot Graph to get  
initial understanding

Perform  
Augmented Dickey-  
Fuller (ADF) test

p-value<=0.05  
(reject H0)  
**STATIONARY**

p-value>0.05  
(accept H0)  
**NON STATIONARY**

BRAVO  
MOVE AHEAD!!

Do Seasonal  
Differencing

ADF test  
again

STATIONARY

NON  
STATIONARY

Other  
techniques

## SARIMA approach

Plot PACF and ACF functions

Moving average order (ACF)

Auto regression order (PACF)

Trained SARIMAX model  
ARIMA order-  
 $(1,1,1)$   
Seasonal order-  
 $(1,1,1,12)$

statsmodels library

- Adfuller
- PACF, ACF
- SARIMAX

Predicted for last 200 rows

Predicted for future 1 year

Predicted for future 5 years

Compared with actual data

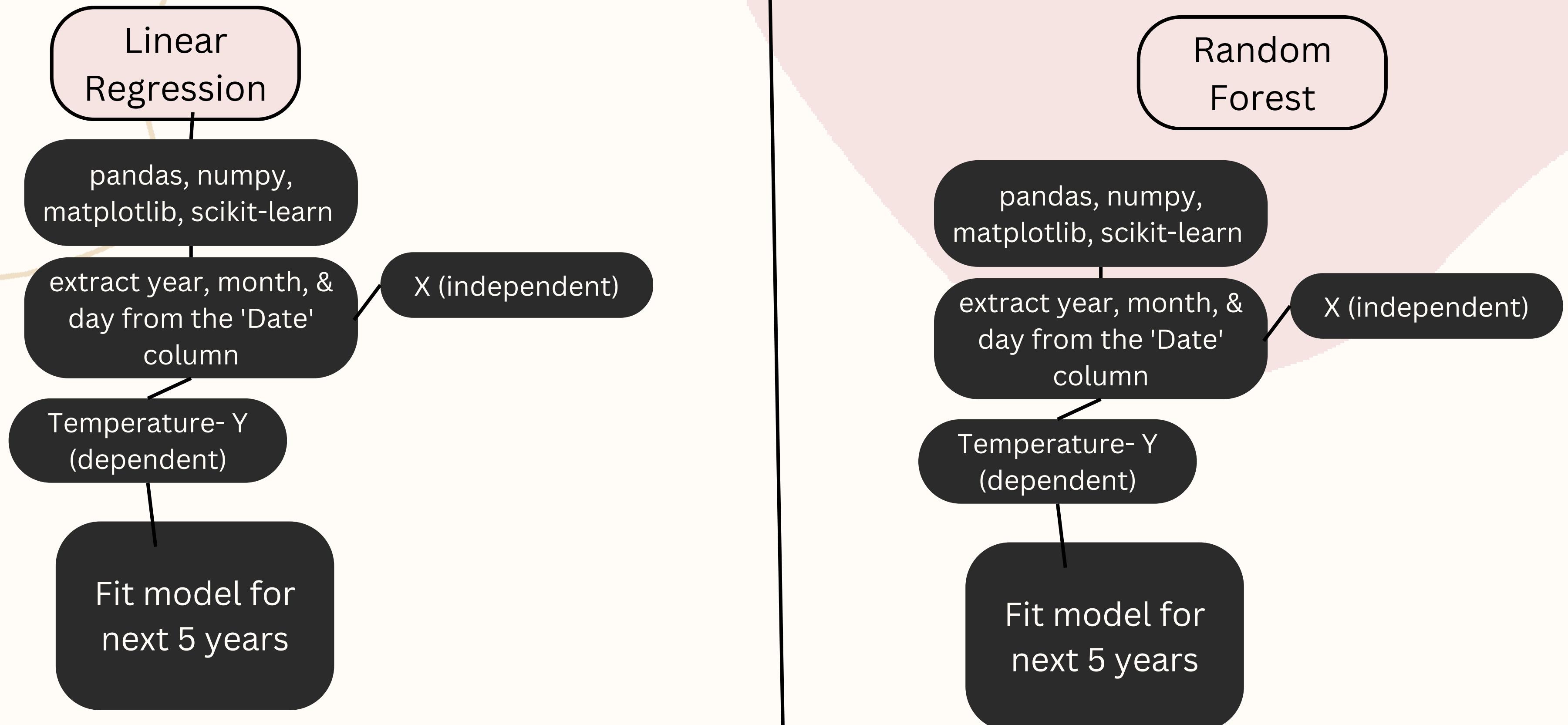
Why SARIMA ? and not ARIMA

SARIMA is preferred over ARIMA and ARMA for temperature time series forecasting because it captures seasonality, which ARIMA and ARMA cannot model effectively.

Why  $(1,1,1,12)$  and not  $(2,0,2)$ ?

tried  $(2,0,2)$ , overfit short-term trends,  
 $(1,1,1)(1,1,1,12)$  improved results - capturing trend and seasonality.

# Linear and Random forest



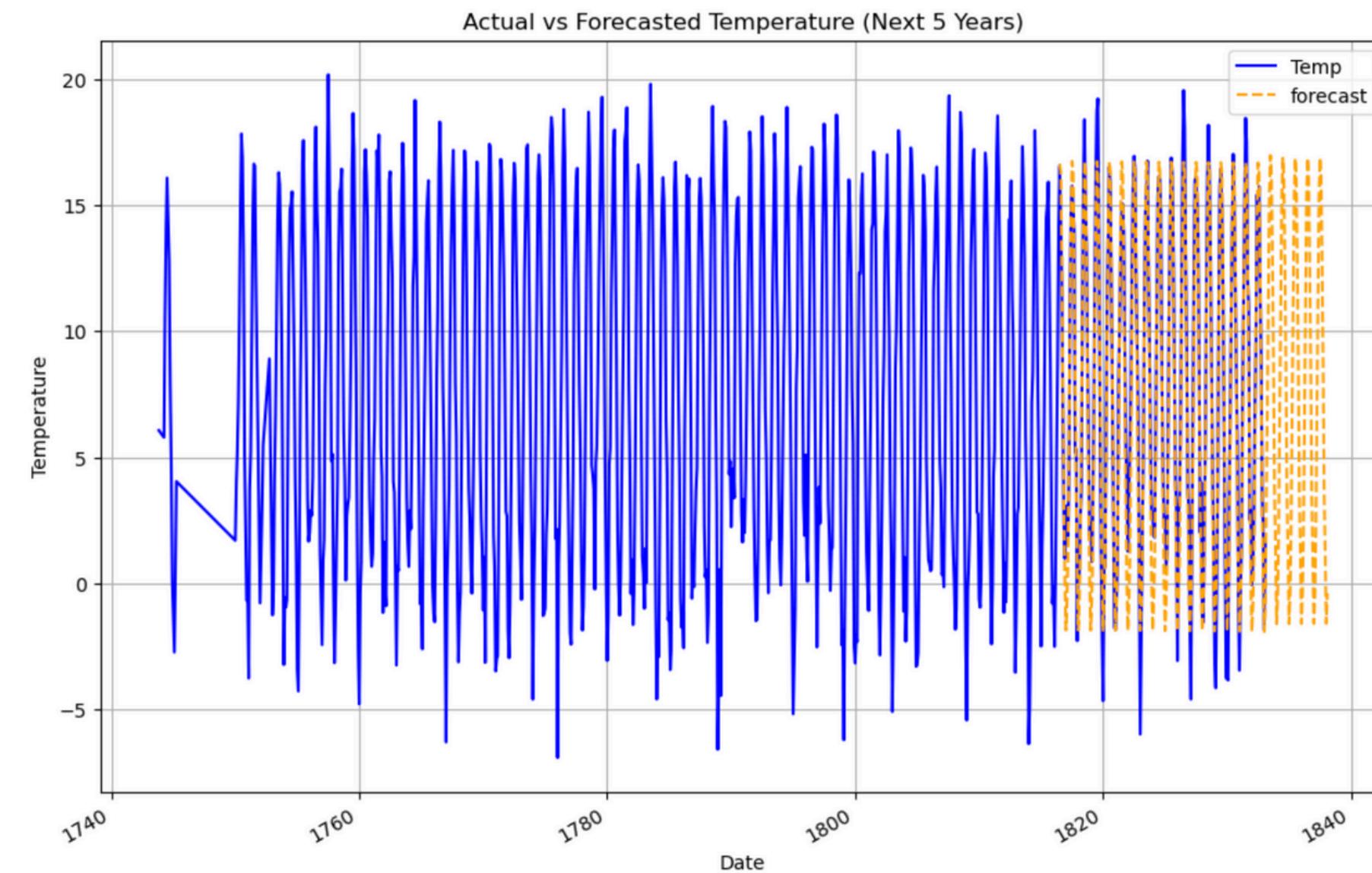
## Results

Model		Temperature	Salinity
Linear Regression	- Training time - Prediction time - MAE - RMSE	-0.0583 seconds -0.0140 seconds -0.3858 -0.5312	-0.0111 seconds -0.0018 seconds -0.3858 -0.5312
Random Forest	- Computation time - MAE - RMSE - R2 score	-0.1449 seconds -0.1101 -0.1497 -0.9290	-0.1556 seconds -0.1101 -0.1497 -0.9290
SARIMA	- Computation time - MAE - RMSE - R2 score	-3.0846 seconds -1.5398 -2.0988 -0.9036	-2.3560 seconds -0.3311 -1.2525 -(-3.9655)

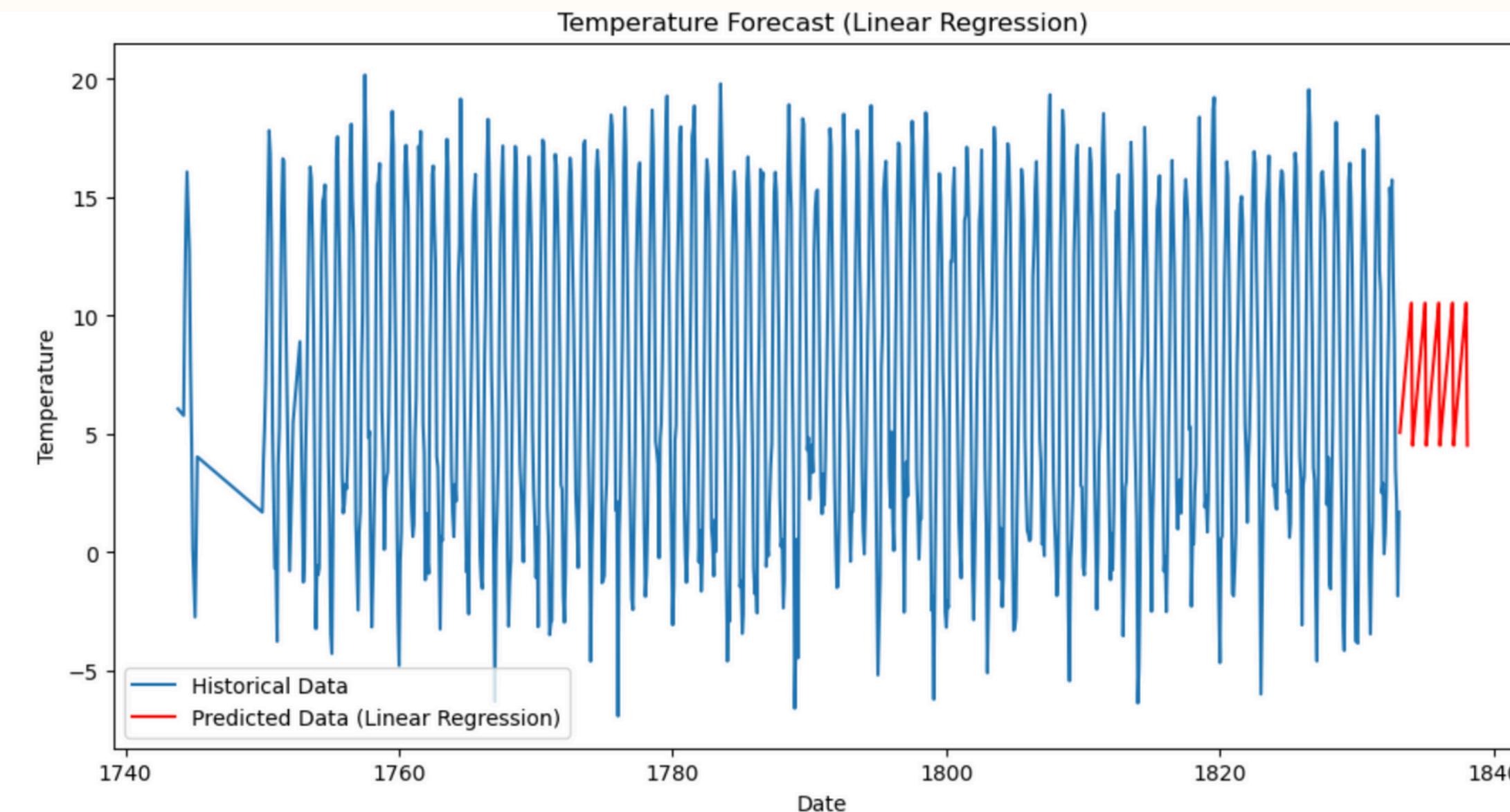
## RESULTS

For salinity, Random Forest performed the best with the lowest MAE (0.1101) and RMSE (0.1497), along with a high  $R^2$  (0.9290), making it the most accurate model. For temperature, SARIMA had the highest  $R^2$  (0.9036), but Random Forest still outperformed in terms of lower MAE (0.1101) and RMSE (0.1497), making it the most reliable choice for both variables.

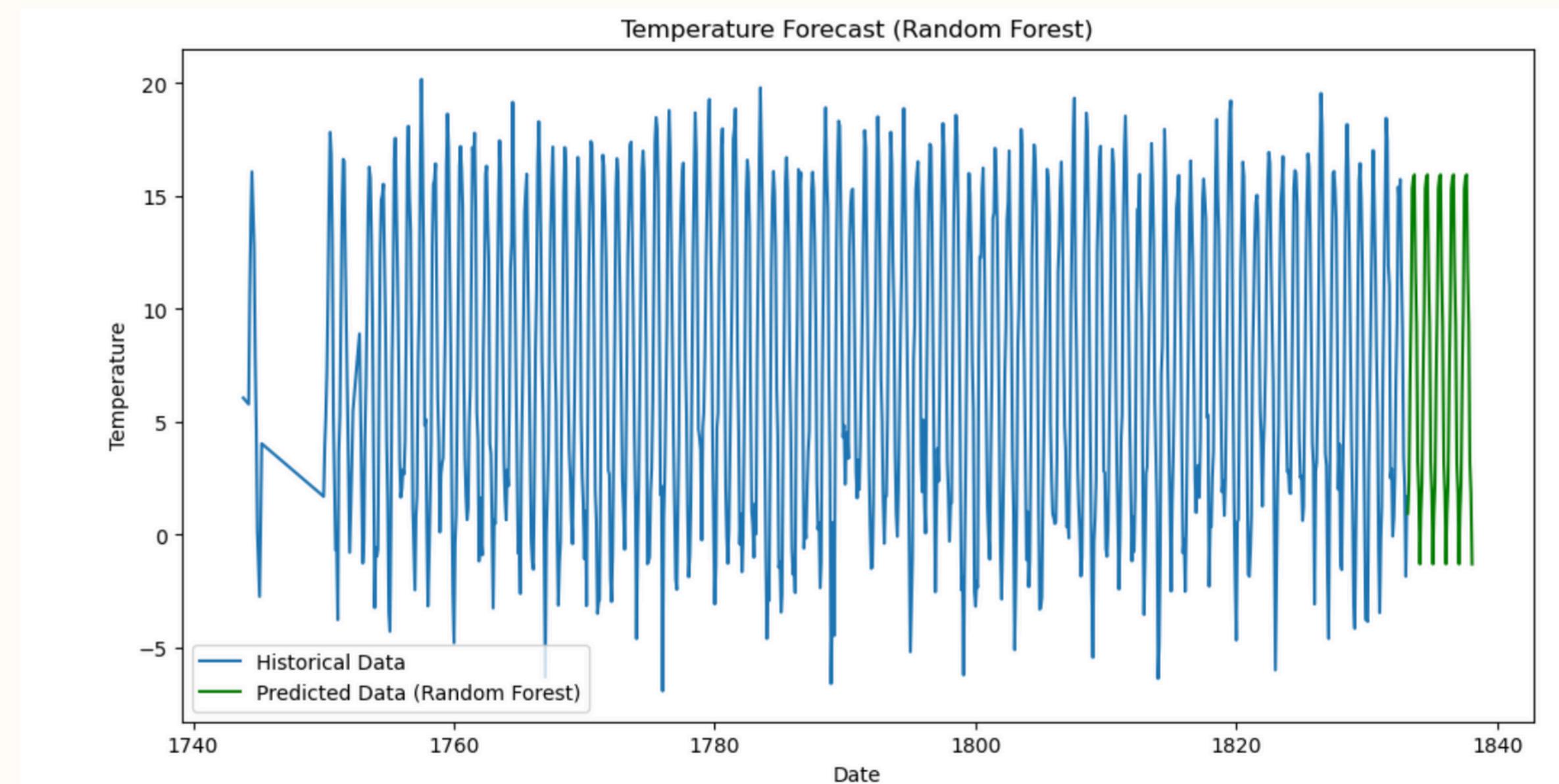
# SARIMA



## Linear



## Random



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link-([https://www.canva.com/design/DAGea3qHKSU/UCeQGySAZA4oefDzbsesEw/edit?utm\\_content=DAGea3qHKSU&utm\\_campaign=designshare&utm\\_medium=link2&utm\\_source=sharebutton](https://www.canva.com/design/DAGea3qHKSU/UCeQGySAZA4oefDzbsesEw/edit?utm_content=DAGea3qHKSU&utm_campaign=designshare&utm_medium=link2&utm_source=sharebutton))

*Thank  
You*

