Time Series Forecast of SST

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01

Motivation

Importance of SST

Ecological Impact

Alter species distributions, food webs, predator/prey relationships, reproductive timing

Human Health Impact

Cause sea level rise increasing erosion, flooding, salt water contamination, beach usage reassessment

Economic Impact

Damage vital infrastructure, force relocation, disrupt fishing practices and markets

02

Background

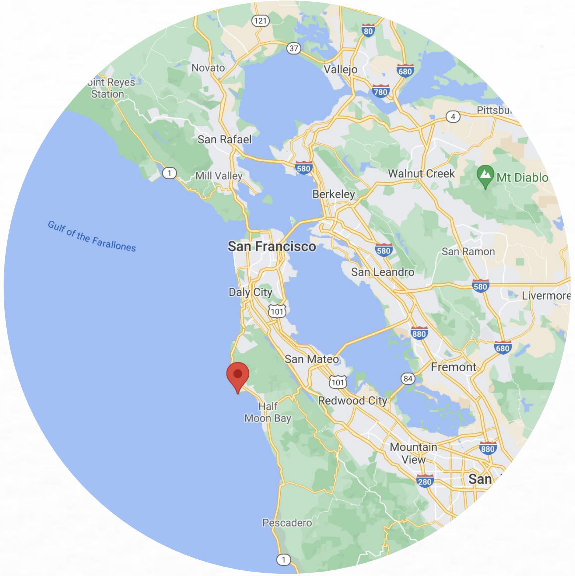
Project Overview

Data

Monthly mean SST anomalies from climatology

Location

Half Moon Bay, CA
Lat, Lon: (37.5, -122.5)



Methods

Time series forecasting accounting for seasonality

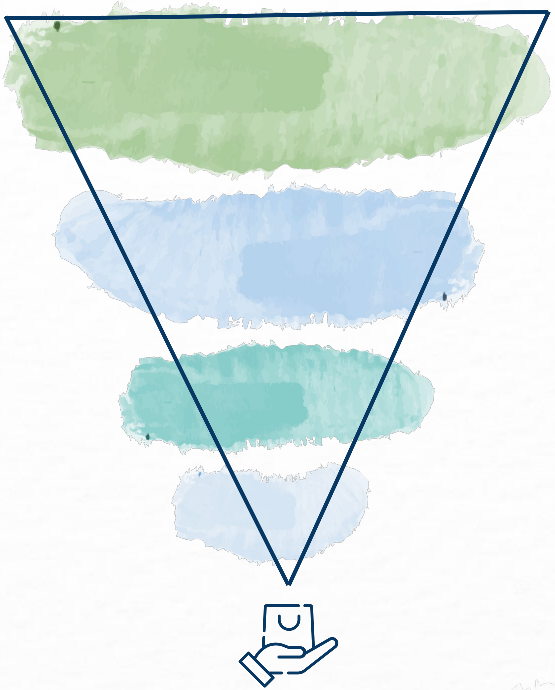
Results

Forecast SST temperature 10 years into future

03

Data

Dataset Breakdown

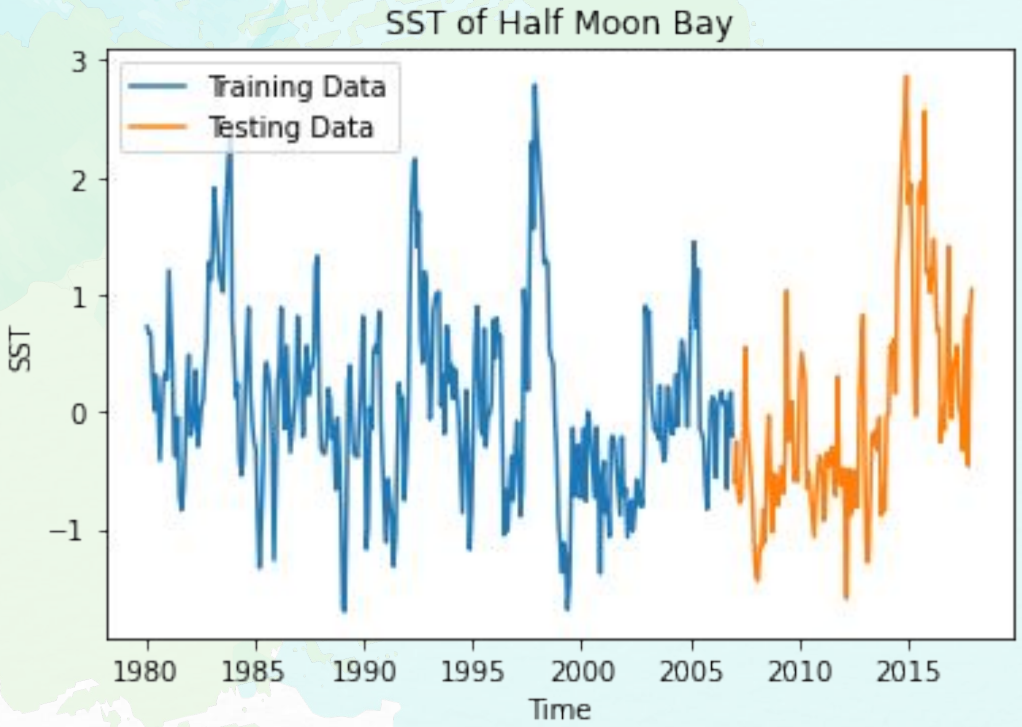


01 **COBE SST Mean Monthly Anomalies**
1880-present, global

02 **Training Data**
1980-2006, Half Moon Bay

03 **Test Data**
2007-2017, Half Moon Bay

04 **Predictions**
2018-2028, Half Moon Bay

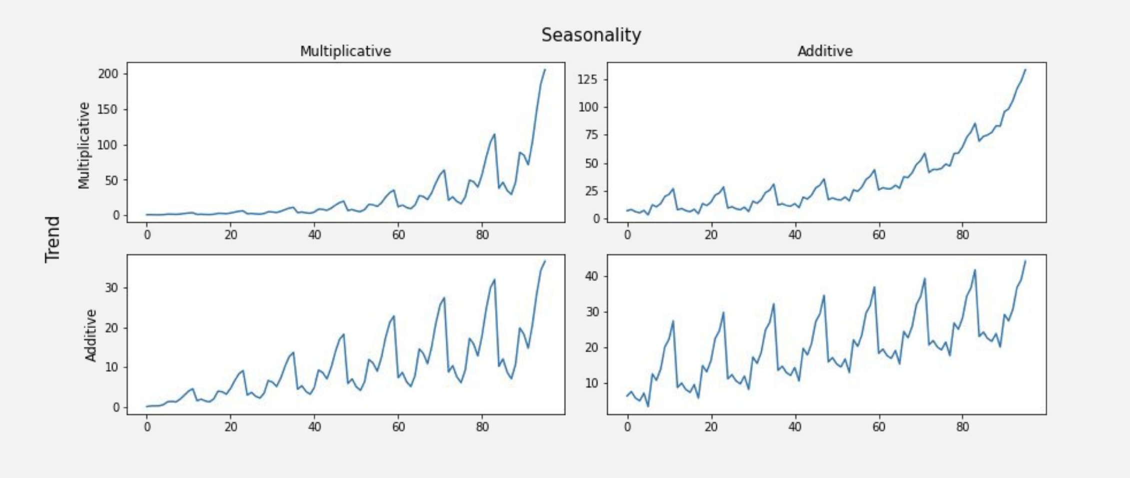

SST of Half Moon Bay
Training Data
Testing Data
SST
Time
3
2
1
0
−1
1980
1985
1990
1995
2000
2005
2010
2015

04

Methodology

Time Series Forecasting

Forecast measured quantity at points in the future based on historical, consecutive observations



Selected Models

01

Triple Exponential Smoothing

- Weighted sum of past observations
- Exponentially decreasing weights for past observations
- Accounts for seasonality

```
# Import model
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

02

SARIMA

- Weighted sum of past observations, differencing, and moving averages
- Accounts for seasonality

```
# Import model
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

03

Prophet

- Non-linear trends fit with seasonality and holiday effects
- Best for data with strong seasonal effects and several seasons of historical data

```
# Import model
from fbprophet import Prophet
```

05

Metrics & Model Selection

Metrics

R^2 Value

Determines goodness-of-fit

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

MAPE

Highlights the relative error

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

MAE

Tells how big of an error you can expect on average

$$\text{MAE} = \frac{\sum_{i=0}^{n} |y_i - \hat{y}_i|}{n}$$

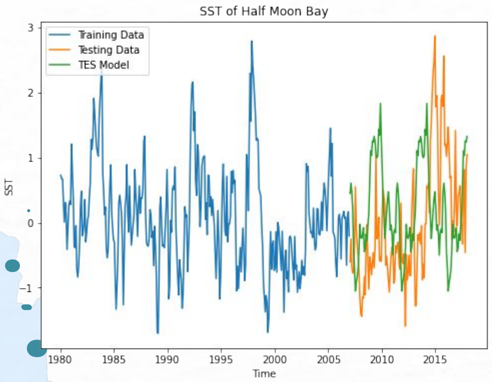
MSE

Highlights large errors or forecasting outliers

$$\text{MSE} = \frac{\sum_{i=0}^{n} (y_i - \hat{y}_i)^2}{n}$$

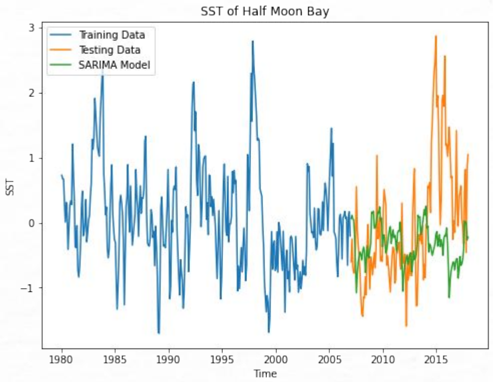
Model Comparisons

Triple Exponential Smoothing



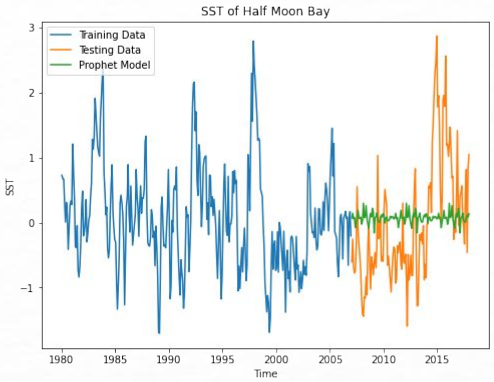

```
------ TES  Model------
R2:  -0.654
MAE:  1.0049
MAPE:  316.2973
MSE:  1.4152
```

SARIMA




```
------ SARIMA  Model------
R2:  -0.2889
MAE:  0.8003
MAPE:  186.4918
MSE:  1.1029
```

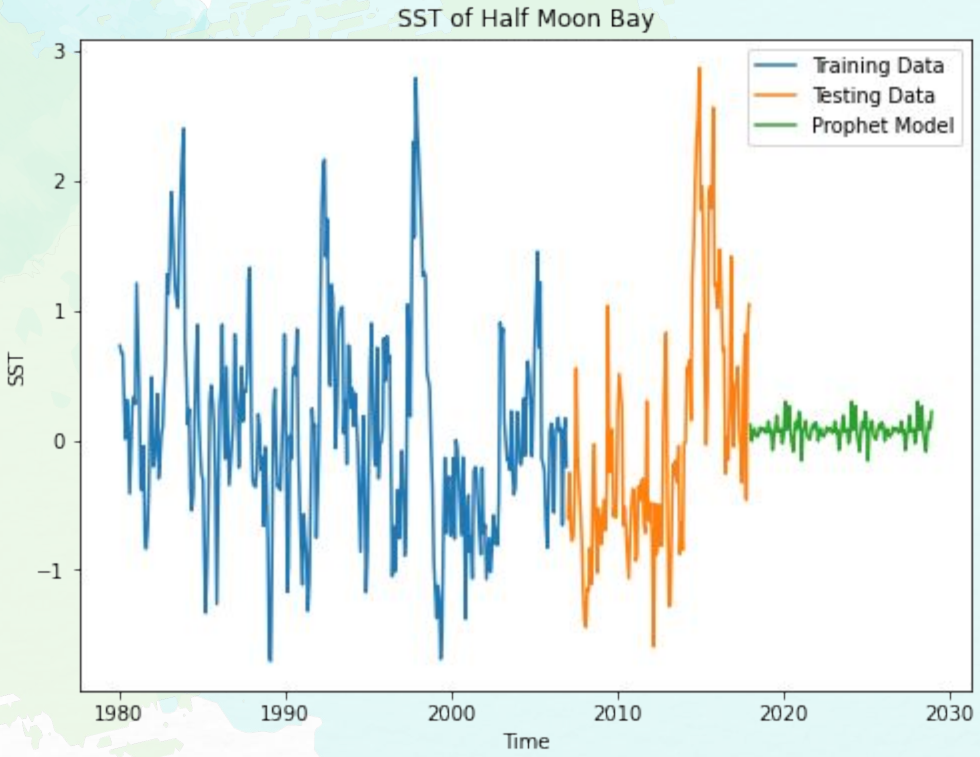
Prophet




```
------ Prophet  Model------
R2:  -0.0078
MAE:  0.7561
MAPE:  114.3487
MSE:  0.8624
```

06

Forecast & Implications


SST of Half Moon Bay
Training Data
Testing Data
Prophet Model
SST
3
2
1
0
−1
1980
1990
2000
2010
2020
2030
Time

Increasing SST Implications

01

Agriculture

Seawater intrusion, flooding, and loss of quality

02

Fishing

Loss of fish species and fishing markets

03

Surfing

Change wave breaks, size, shape, and density

Thank You!