Global Surface Temperature
05/27/2025

Climate change is one of the major threats to the human society today. One of the key drivers, based on the current scientific research, is the "greenhouse gas" emission from human activities, including burning fossil fuels as a result of power generation, transportation, steel making, cement making, and other industrialization activities. The increased concentration of the green house gas in the atmosphere reduces the thermal radiation from the Earth surface therefore increases the global surface temperature over the years (see Figure 1). The data series in the figure is from the NASA Goddard Institute for Space Studies (GISS). They are the temperature "anomalies" relative to the 1951–1980 mean when the average temperature is regarded as "nominal". The consequences of earth surface temperature increase are server weather pattern changes across the globe, glacial and polar ice melting, and the rise of the sea level.

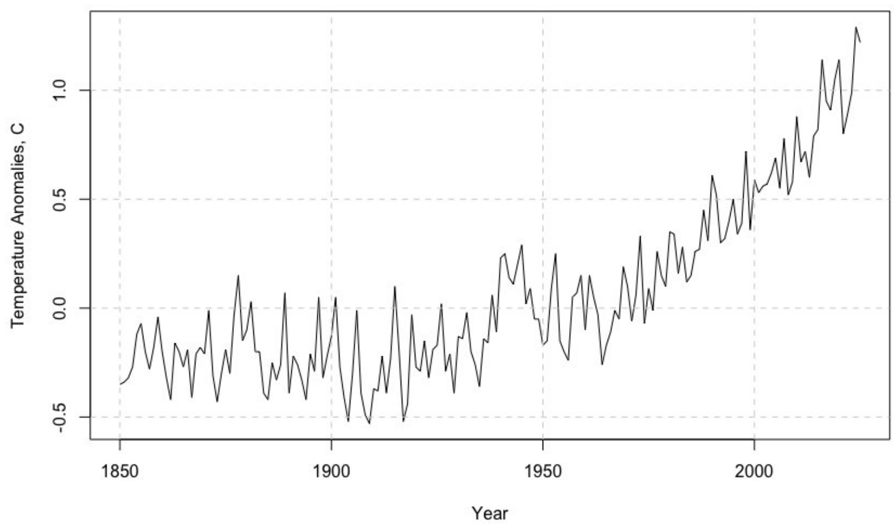

Figure 1, Global Surface Temperature Anomalies.

As the "Paris Agreement" in 2015, a global temperature target is established to keep the temperature anomalies below 2°C, and further try to limit them to 1.5°C which could reduce the impact of the climate change. The anomaly is currently at 1.22°C in 2025.

Time Series Forecast

The historical data could help to predict the future global temperature anomalies assuming no drastic change in human activities over the time. The immediate need is to forecast the temperature anomalies in the next decade so that mitigating measures can be planned to lessen the impact of the global temperature rise. There are two major categories in the forecasting methods. One is the classic statistical methods that rely on ARIMA models and the State Space models. The other is the Machine Learning methods that train models like the Random Forest, Gradient Boosting Machine, and Support Vector Machine. This article examines the methods in the first category.

ARIMA Model

Autoregressive integrated moving average (ARIMA) model is regarded as the general model for any time series. Mathematically, a stationary time series can be expanded into either an infinite autoregressive series or an infinite moving average series. For a practical model with limited terms, A time series can be expressed as a combination of a finite AR term and a finite MA term. The employment of difference (aka "integrated") is to treat the trend in a time series. As such, an ARIMA model is expressed as ARIMA(*p,d,q*) where *p, d,* and *q* are the orders of AR, Difference and MA terms.

$$\phi(L)(1-L)^d X_t = \theta(L)\epsilon_t$$

where $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 \cdots - \phi_p L^p$ is the AR(p) term, $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$ the MA(p) term, $(1-L)^d$ the d-th order of differencing term, and L the lag operator.

Figure 2 shows an ARIMA(4,1,0) model fitted with data from 1970 to 2015 and the forecast temperature anomalies of 2015 through 2025 (blue line with the prediction intervals) against the actuals (red line).

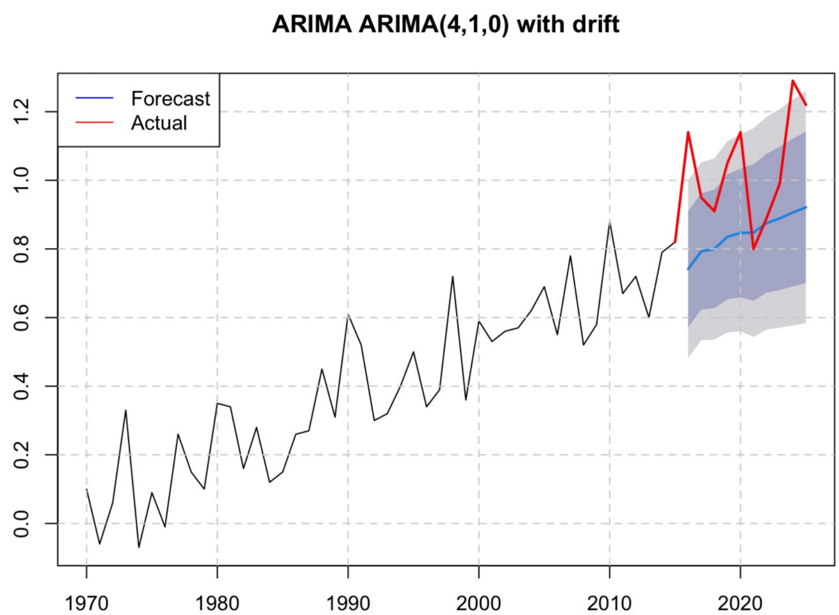

Figure 2, ARIMA Model of Global Surface Temperature Anomalies.

ETS Model

ETS is a state space model that decomposes a time series into error (E), trend(T) and seasonality (S) either as additive (A) or multiplicative (M) terms. Holt-Winters model is a specific second-order, additive exponential smoothing ETS model. The Holt-Winters model without the seasonality term is demonstrated below. The state space variables L and T are computed using the "double exponential smoothing" procedure where y_t is the time series value at time t; α and β are parameters to be determined.

$$L_t = \alpha y_t + (1-\alpha)\left(L_{t-1} + T_{t-1}\right)$$
$$T_t = \beta\left(L_t - L_{t-1}\right) + (1-\beta)T_{t-1}$$

The one-step ahead forecast value is the combination of the state space variables L and T at time t.

$$\hat{y}_{t+h} = L_t + T_t$$

Figure 3 shows the Holt-Winters model without seasonality fitted the global surface temperature anomalies from 1970 to 2015 and the forecast values from 2015 to 2025 (blue line with the prediction intervals). The red line is the actual surface temperature anomalies from 2015 to 2025.

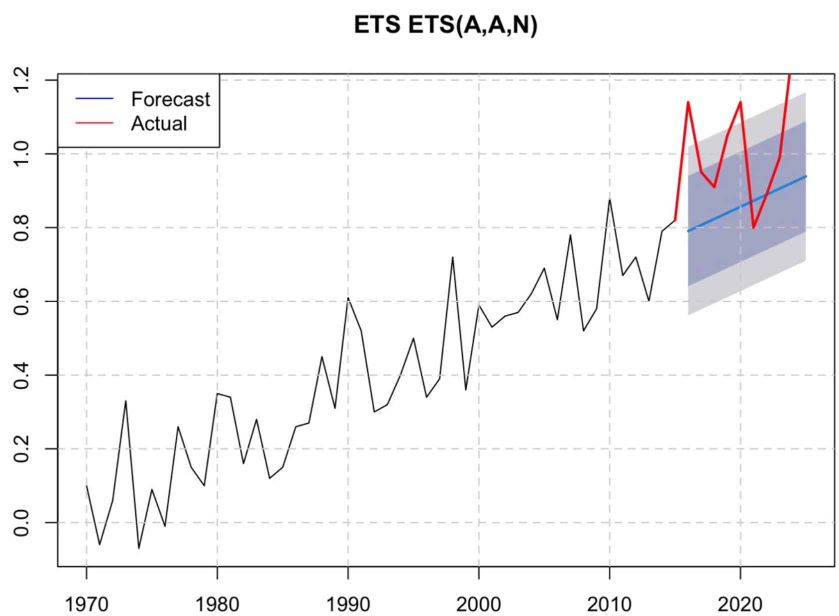

Figure 3, ETS Model (specifically Holt-Winders model) of Global Surface Temperature Anomalies.

Figure 4 and 5 are the numerical values of the forecast and the prediction intervals for the next decade using the ARIMA and Holt-Winters models. As suggested by these models, in 2035 (ten years from now), the global surface temperature anomaly will be between 0.95 and 1.82 °C as the 95% prediction interval. However, these models treat the historical global surface temperature series as the only information source for the prediction. Therefore, the models are of a "univariate." As we know, the human society has debated the global warning phenomenon for a quite some time. In recent years, some human interventions on the greenhouse gas emissions have taken place and additional measures have been planned in the future. Noticeably, the renewable energy revolution, electric vehicle adoption, and even carbon capture projects have just started across the globe. These efforts will likely bring a positive impact to slow down the rate of increase in the greenhouse gas concentration in the atmosphere. These effects are not included in the historic data and not reflected in the above model predictions.

```
     Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
2026       1.136944 0.9474103 1.326477 0.8470774 1.426810
2027       1.205909 1.0102345 1.401584 0.9066505 1.505168
2028       1.270581 1.0680371 1.473124 0.9608170 1.580344
2029       1.260963 1.0458033 1.476123 0.9319046 1.590022
2030       1.267053 1.0321348 1.501972 0.9077765 1.626330
2031       1.302265 1.0581606 1.546370 0.9289395 1.675591
2032       1.327882 1.0739478 1.581816 0.9395233 1.716240
2033       1.340781 1.0756572 1.605905 0.9353091 1.746253
2034       1.360243 1.0840730 1.636412 0.9378776 1.782608
2035       1.384247 1.0988033 1.669690 0.9476987 1.820795
```

Figure 4, ARIMA Forecast of Global Surface Temperature Anomalies in the Next Decade.

```
Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
2026       1.092276 0.9205827 1.263969 0.8296937 1.354858
2027       1.122882 0.9511283 1.294635 0.8602076 1.385556
2028       1.153487 0.9815990 1.325375 0.8906069 1.416368
2029       1.184093 1.0119651 1.356220 0.9208462 1.447339
2030       1.214698 1.0421971 1.387200 0.9508804 1.478516
2031       1.245304 1.0722661 1.418342 0.9806655 1.509942
2032       1.275909 1.1021441 1.449675 1.0101583 1.541660
2033       1.306515 1.1318040 1.481226 1.0393176 1.573712
2034       1.337121 1.1612199 1.513021 1.0681037 1.606137
2035       1.367726 1.1903678 1.545084 1.0964800 1.638972
```

Figure 5, Holt-Winters Forecast of Global Surface Temperature Anomalies in the Next Decade.

Appendix R Script

```
library(forecast)
input=function(fn){y=read.table(fn,header=F,sep=",");ts(y[,2],
start=y[1,1],end=y[nrow(y),1])}

ts_data1=input("temp.csv")
ts_data=window(ts_data1,start=1970)

train_size <- length(ts_data) - 10
train_data <- window(ts_data, end = c(2015))
test_data <- window(ts_data, start = c(2015))

arima_model <- auto.arima(train_data, seasonal = FALSE, stepwise
= TRUE, approximation = TRUE)
arima_forecast <- forecast(arima_model, h = 10)

plot(arima_forecast, main = paste("ARIMA",
toString( arima_model))); grid(lty=2)
lines(test_data, col = "red", lwd = 2)
legend("topleft", legend = c("Forecast", "Actual"), col =
c("blue", "red"), lty = 1)
```

Figure 6 ARIMA Forecast Script

```
hw_model <- holt(train_data)
hw_forecast <- forecast(hw_model, h = 10)

plot(hw_forecast, main = "Holt-Winters"); grid(lty=2)
lines(test_data, col = "red", lwd = 2)
legend("topleft", legend = c("Forecast", "Actual"), col =
c("blue", "red"), lty = 1)
```

Figure 7 Holt-Winters Forecast Script