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Economics & Social Sciences/ Institute of Economics/ Econometrics & Statistics

Modeling and Forecasting of Global Temperature

Herp, Matthias

Introduction

„BASF stellt TDI-Produktion im Ludwigshafen wegen Niedrigwasser ein“

(finanzen.net 26.11.18)

„ (…) rund 50 Millionen Euro niedrigeres Betriebs-ergebnis - bedingt durch höhere Transportkosten und Produktionsverluste. “

(spiegel.de 26.11.18)

„ (…) Pegelstand von 40 Zentimetern erreichen drei Viertel unserer Flotte nicht mehr die Häfen Amsterdam und Antwerpen", sagt der Geschäftsführer der Contargo Rhein-Neckar GmbH “

(rnz.de19.10.18)

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   1.3 Quadratic Trend M3
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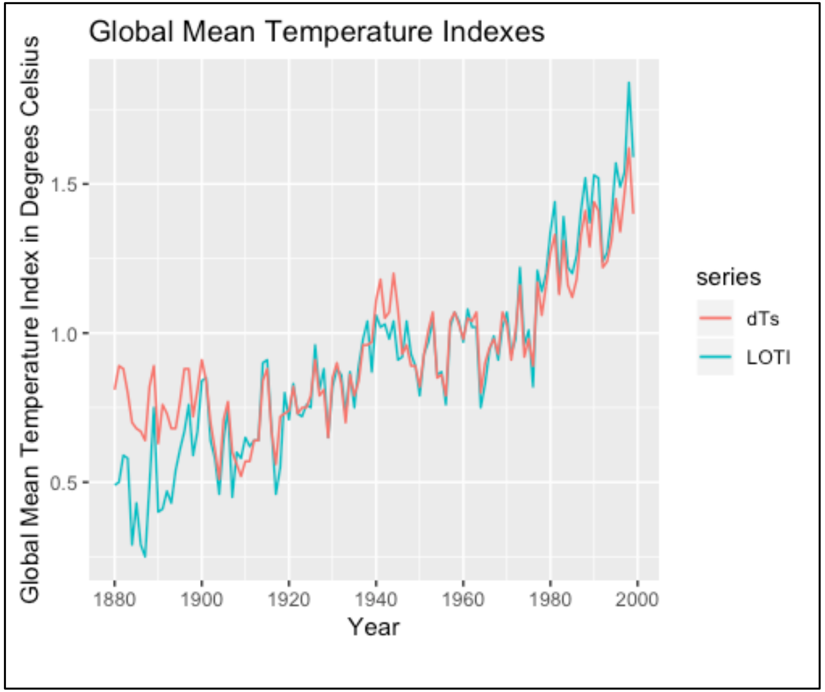
Data Sets

2 Data Sets from the GISS surface temperature analysis published by NASA:

-LOTI: Land-Ocean Temperature Index

-dTs: Meteorological Station Data Index

Global temperature anomaly indexes: base value of ”1” - equal to the mean over 1951-1980



Model Frameworks and Estimations

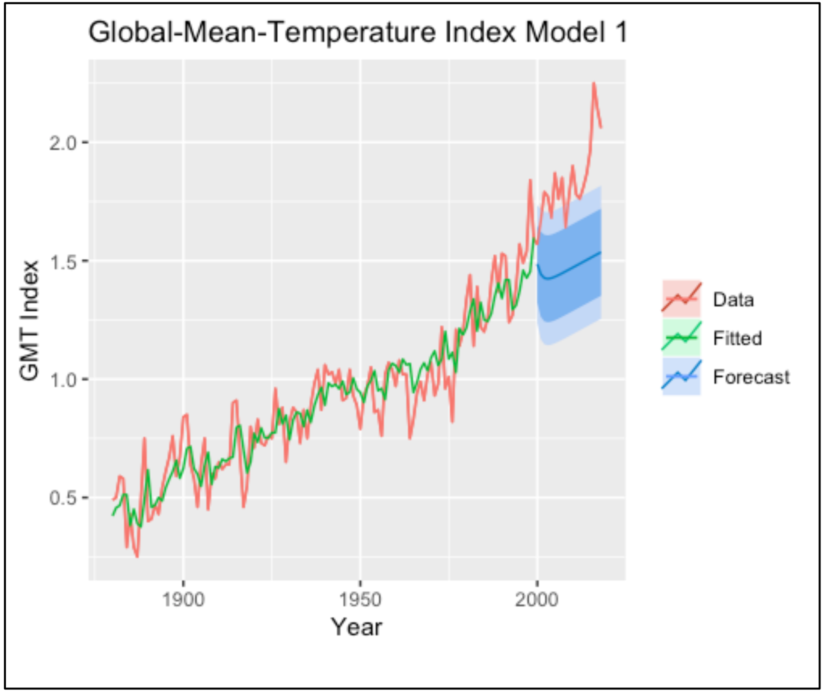
Linear Trend M1

β_0: Intercept

$\beta_1 t_0$: Linear Time Trend

$$GT_t = 0{,}464 + 0{,}008 t_0 + 0{,}406 GT_{t-1} + \varepsilon_t$$

ϕ_1: Autoregressive Error



Linear Trend Shift M2

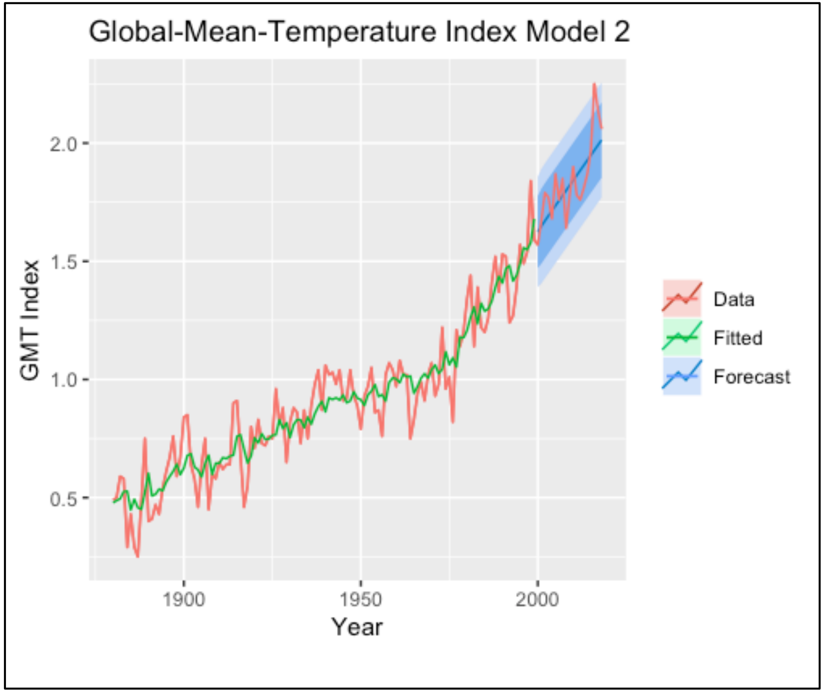
β_0: Intercept

$\beta_1 t_0$: Linear Time Trend

$$GT_t = 0{,}472 + 0{,}006t_0 + 0{,}015t_1 + 0{,}286GT_{t-1} + \varepsilon_t$$

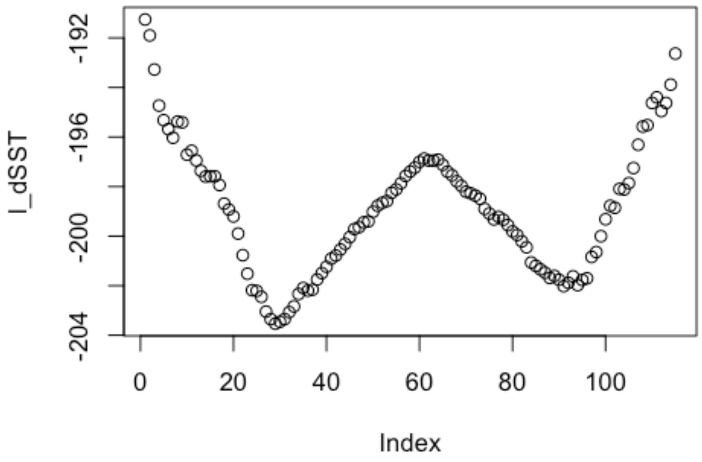
$\beta_2 t_1$: Linear Trend Shift

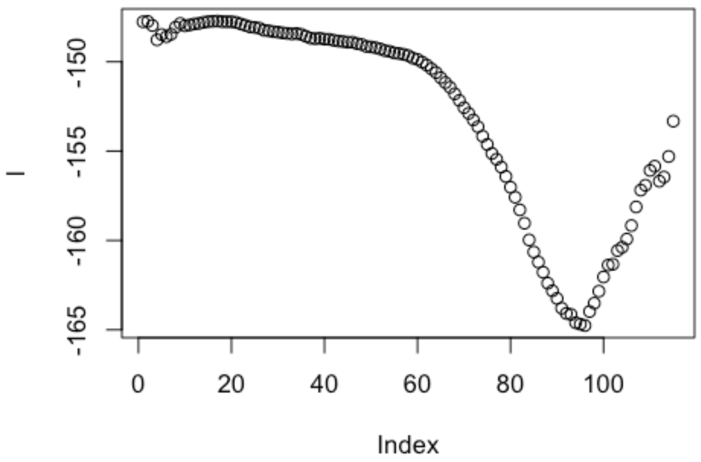
ϕ_1: Autoregressive Error



AIC Minimization

$$AIC(t_s) = AIC(GT_t = \beta_0 + \beta_1 t_0 + \beta_2 t_1(t_s) + \varepsilon_t)$$





Quadratic Trend M3

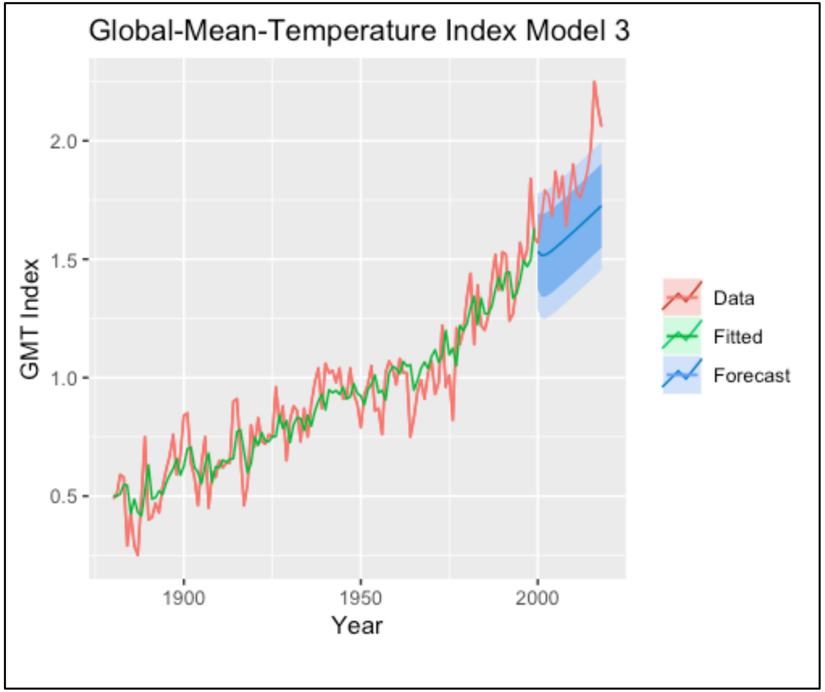
β_0: Intercept

$\beta_1 t_0$: Linear Time Trend

$$GT_t = 0{,}500 + 0{,}003t_0 + 3{,}9e^{-5}{t_0}^2 + 0{,}418GT_{t-1} + \varepsilon_t$$

$\beta_2 {t_0}^2$: Quadratic Trend

ϕ_1: Autoregressive Error



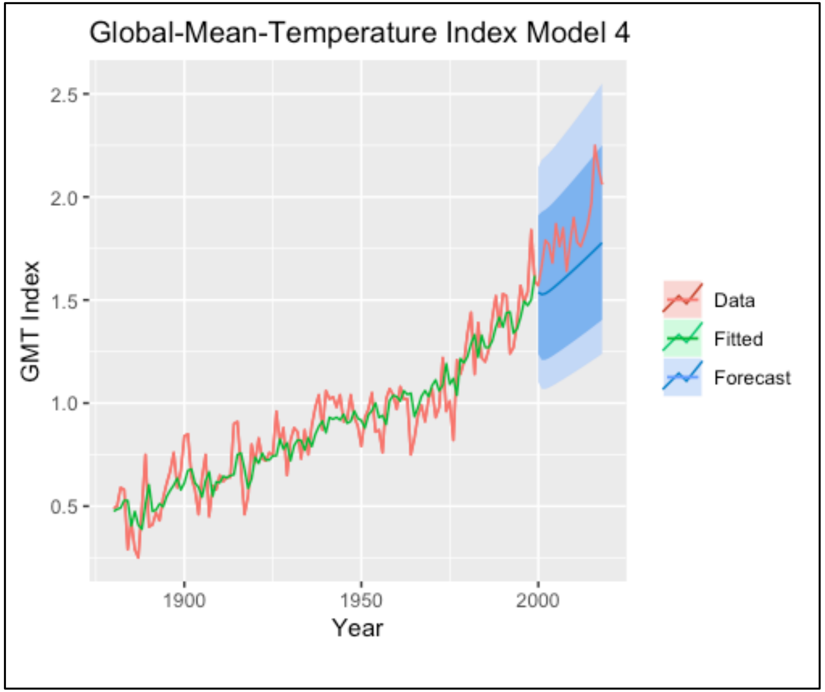
Exponetial Trend M4

β_0: Intercept

$\beta_1 t_0$: Exponetial Time Trend

$$GT_t = e^{-0{,}755+0{,}010t_0} + 0{,}391GT_{t-1} + \varepsilon_t$$

ϕ_1: Autoregressive Error



Model Comparison

Comparison

In-sample goodness of fit is measured by the Akaike and Bayesian information criteria:

SSE: sum of squared errors
k: total number of parameters

$$AIC = \mathrm{T}\log\left(\frac{SSE}{T}\right) + 2(k+2)$$

$$BIC = \mathrm{T}\log\left(\frac{SSE}{T}\right) + (k+2)\log(T)$$

smaller AIC and BIC: better in-sample fit

LOTI Data Set

	AIC	BIC
m1	-149.658797576938	-138.508830605809
m2	-164.604797991063	-150.667339277153
m3	-152.154356658756	-138.216897944846
m4	-80.3747785300581	-69.2248115589299

dTs Data Set

	AIC	BIC
m1	-193.208532967406	-182.05856599627 8
m2	-201.605667400586	-187.668208686676
m3	-202.752110316296	-188.814651602386
m4	-165.825398371563	-154.675431400435

Comparison

The **out-of-sample prediction power** measured by the root mean squared error and the mean absolute forecasting error:

$$RMSE = \sqrt{\left(\frac{1}{T} SSE\right)}$$

$$MAFE = \frac{1}{T} SSE$$

smaller RMSE and MAFE: better forecast

LOTI Data Set

	RMSE	MAFE
m1	0.116774535745137	0.0964958941293507
m2	0.0773010864638682	0.0632416297875762
m3	0.0824228796593032	0.0658092066525089
m4	0.116774535745137	0.0964958941293507

dTs Data Set

	RMSE	MAFE
m1	0.116774535745137	0.140472483330205
m2	0.0773010864638682	0.0801950296321266
m3	0.0824228796593032	0.0975460991615205
m4	0.116774535745137	0.140472483330205

Comparison

The **model implications** are examined by looking at the trend assumptions and judging if they are feasible:

The quadratic and exponential trends imply increasing growth

The linear trend models imply constant growth

In my opinion a constant growth in global temperature appears to be the more prudent and realistic assumption.

"It is not recommended that quadratic or higher order trends be used in forecasting. When they are extrapolated, the resulting forecasts are often unrealistic.

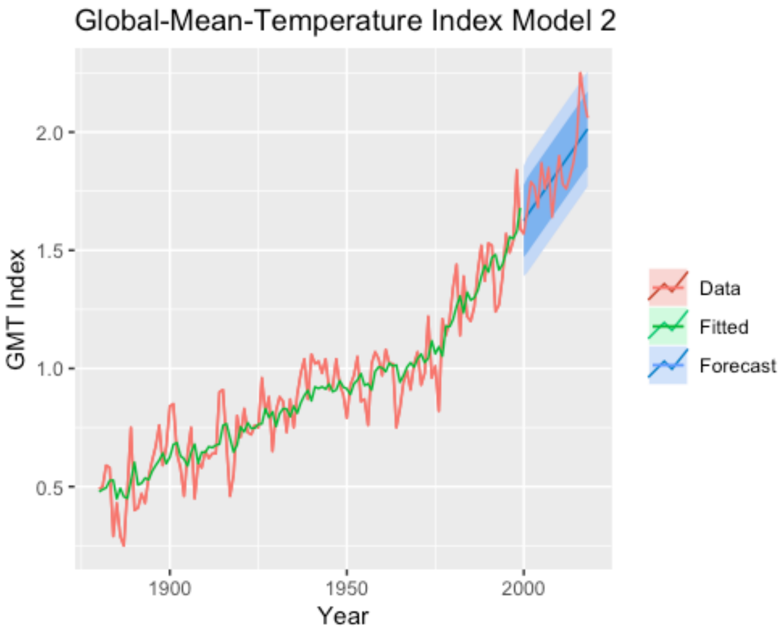
A better approach is to use (…) a piecewise linear trend which bends at some point in time. "
(Hyndman, R.J., & Athanasopoulos, G., 2018, Sec 5.8)

Conclusion

Conclusion

The **linear trend shift model** is best model:

1. It provides the overall best fit
2. It provides the best forecast
3. The underlying assumption is sound for global temperature data



Conclusion

Next steps can be different…

1. Models: Optimizing of a higher order Trend, Exponential Smoothing, Vector Autoregressive…
2. Data Sources: seasonal observations, local scale, other climate parameters…

Model Limits are the…

1. Data Sets: multiple sources combined and transformed, unequal distribution of metrological stations…
2. Time Frame: limited to 139 Years
3. Trend Assumptions: linear, quadratic, exponential…

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Thank You for Your Attention!

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