

# Global temperature and rising sea levels in Sweden from 1886-2020

Joseph Eriksson

15 Maj 2022

## Introduction

Since the industrial evolution humankind have emitted a lot of different kind of emissions into our oceans and atmosphere. Carbon emissions especially have since lead to an increase in the global temperature in the atmosphere and Ocean leading to climate change.

Sea levels are now rising and are expected to rise for centuries even with greenhouse emissions being curbed and their atmospheric concentrations stabilized (John A. Church, 2011). We are now observing a warming ocean and hence ocean thermal expansion. Other ways global warming is affecting sea level is through melting of land ice such as glaciers and ice caps which mainly come from Antarctica and Greenland.

Due to global warming being a global problem we should also expect it to affect the ocean level near Sweden. We will therefore study this link by looking at changes the ocean levels for Sweden and changes in the global temperature since 1800s. We will further analyze and test this link between global warming and rising sea levels using time series analysis on sea levels in Sweden and global temperature looking at both short- and long-term relationships.

An article from Göteborgs-posten stated that some parts of Göteborg city will be under water if the ocean level increases by 2.3 meters from 2011 sea level (Göteborgs-posten, 2011). We will therefore also do a forecast to see which year our models estimate we reach that level to better understand the time horizon of our problem.

The scientific articles have established a causal link where global warming leads to rises in sea level and not the way around. Between the variable's sea level and global temperature so we expect there to be a positive correlation between the variables and we also expect both variables to have a positive trend over time. We therefore expect both variables to be trend stationary of order 1.

## Data

Annual dataset with the change in sea level (cm) for the mean of 14 Swedish measuring stations between 1886-2019 (135 obs) adjusted for the effect of rising land levels. Source: Swedish Meteorological and Hydrological Institute (SMHI). Annual dataset between 1886-2019 where temperature anomalies are based on the HadCRUT4 land-sea dataset as published by the Met Office Hadley Centre. Temperature anomalies are given in degrees Celsius relative to the average temperature over the period 1961-1990.

## Results

Following the work process for the bivariate case we start by testing for order of stationarity. Observing the data shown in figure 2 from the annex, and we can tell that the data is not stationary. This can more formally be tested through the ADF-test where it estimates 3 different equations: first (tau3) is with drift and trend, second (tau2) is with drift only and third (tau1) is with neither drift nor trend.

Looking at table 1 we see that we reject the null of a unit root only for the equation with drift and trend, so we therefore take the first difference. After taking the difference we did another ADF-test shown in table 2 and we rejected the null for the model with no trend or drift. Which means that Sea level variable is first difference stationary. This slightly changes our interpretation of the variable to changes in sea level or sea level rise/fall.

Doing the same thing for our global temperature variable we found that we could not reject the null for any equation shown in table 3. However, after taking the first difference and perform the ADF test again we get results shown in table 4 where we could reject the null of a unit root for all models. Which means that the global temperature variable is also first difference stationary. Because we have 2 variables that are integrated of order  $I(1)$  we have to test for cointegration to see if they share a stochastic process. Interpretation also changes from temperature anomalies to changes in temperature anomalies when we use the first difference data. Positive change in temperature anomalies can synonymously be interpreted as changes in global temperature.

We begin the process of testing for cointegration through the Engle-Granger ADF-test. For this test we have to use different critical values that follow a specific distribution. For 5% significance level and single cointegration relationship, the critical value is -3.41 given to us by (James Stock). From the results given to us in table 5 we see that our test statistic is larger than our critical value, we thereby reject the null that the residuals have a unit root. According to the Engle-Granger ADF-test we can therefore conclude that changes in sea-levels and global temperature are cointegrated. It is therefore possible to estimate a vector error correction model (VECM).

I estimated an VECM model with the “no trend and drift model” and lag order 3 suggested by SC & HQ information criteria and cointegrating level of 1 using 2OLS as estimator. The VECM allows the long run behaviour of the endogenous variables to converge to their long run equilibrium relationship while allowing a wide range of short run dynamics. The VECM model with first difference sea level variable had statistically significant results on 1 % significance level for the long-term error correction term (ECT) estimate which was estimated to be -3.08 which can be interpreted as the speed of convergence to equilibrium is 308%. Thus, in the short run, Sea level change is adjusted by 308% of the past years deviation from equilibrium which would imply that sea level change return to equilibrium values within a year. This is not really an expected result; it is rare that the ECT is not between 0-1 which would indicate potential issue with the model specification.

In order for us to transform the VECM into a Var model we have to perform a trace- and maximum eigenvalue test that we use to determine how many cointegration relationships there are. Then the VAR model was used to create an impulse and response function (irf) that we can use to determine the short- and long-term effect on sea level changes when we shock change in temperature anomalies with 1 standard deviation.

The cumulative irf figure 3 seem to suggest that increase in global temperature change with 1 standard positively effects sea level rise and we also observe a positive feedback loop that perpetuate itself. I expected a positive reaction which was the case but not this feedback loop. I would argue that we cannot take this positive feedback loop into the extreme time horizons because this would imply that an increase in global temperature would in the infinite time horizon lead to infinite increase in sea level which is unreasonable, the data generating process would be vastly different at that point which would render this model irrelevant.

In figure 4 we get similar interpretation as in the cumulative model however we do not add up the cumulative effect over time in this case. With a 95% confidence for all time periods within the plot except for  $t=4$ , we have statistically significant and positive result. The results implies that a standard deviation shock in global temperature change is estimated to positively effect sea level rise and to stay positive over a longer period of time. The effect on sea level was approximately 2.1 cm in year 3 and 1.37 cm in year 20.

To determine how good fit the VAR model is to the data we do a Ljung-box and Jarque-Bera test. When we performed the Ljung-Box test for autocorrelation we got a p-value less than 5% which implies that we reject the null of no autocorrelation in favour of  $H_1$  that we have autocorrelation in our residuals. For the Jarque-Bera normality test we got a p-value above 5% for the simultaneous skewness and kurtosis test which means that we do not reject the null of normality for the residuals. It's not good that we still have autocorrelation left in our residuals, this means that we still have systematic variation left that we do not take into account in our model which indicate bad fit. However, it's good that the residuals at least are normally distributed.

Comparing the forecasts in figure 1 and 5 we see that the auto arima model that only base forecasts on previous levels of sea level was the most optimistic. For that model it would take over a millennium for Gothenburg to be under water. But this model lacks to take into account rising levels of global temperature of different degrees which is why the forecast from the EEA predicted it would take much less time. The EEA forecast also takes into account that our emission level is very unpredictable and due to this uncertainty, we have a very large span of outcomes that are given certain levels of emission over the years. Just graphically looking at the EEA forecast we can see that given very high emission levels Gothenburg can be under water in under 130 years. However, this under the assumption that the increase in ocean level that are shown in the figure effects the ocean level near Gothenburg by the same amount.

## Conclusion

Our models are very much in line with theory and suggest that we as global temperature have risen over the past years, we expect rising sea levels where the shocks in global temperature expect to effect sea level in the short run. However, over the long run we expect sea level to converge toward an equilibrium generally within a year, which implies a steady and smooth evolution of sea level with small changes over time which is in line with how sea level has changed previously since the 1800s. An unexpected result was that we expect increases in global temperature to give rise to positive feedback loops that increases sea levels further in an infinite loop.

The result indicates increasing sea levels over time given that global temperature continues as it has been over the last 2 centuries. However depending on what models we use or what we expect in the future given emission levels or other factors that effect global temperature we get vastly different forecast estimates on when Gothenburg will be under water ranging from approximately 130 years up to over 1000 years giving us a large uncertainty range and room for both optimism and pessimism.

The exact results should be taken with a grain of salt but overall, the sign of the effects and somewhat the effect if its small or large seem to be in sync with theory which is promising. We should however consider in our conclusion that we found indicators for our VECM and VAR models that suggested bad fit and that is probably something that can be improved if we want more precise results.

## Referenser

Göteborgs-posten. (den 9 juni 2011). *Skräckbilden visar ett Göteborg under vatten*. Hämtat från <https://www.gp.se/nyheter/g%C3%B6teborg/skr%C3%A4ckbilden-visar-ett-g%C3%B6teborg-under-vatten-1.826430>

James Stock, M. W. (u.d.). Introduction to Econometrics. i , *Table Table 17.1* , p. 665 (4 uppl.). Pearson.

John A. Church, N. J. (2011). *Sea-Level Rise from the Late 19th to the Early*. Switzerland: Springer Nature Switzerland AG.

Morice, C. P., J. J. Kennedy, N. A. Rayner, and P. D. Jones (2012), Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 dataset, J. Geophys. Res., 117, D08101, doi:10.1029/2011JD017187.

## Annex

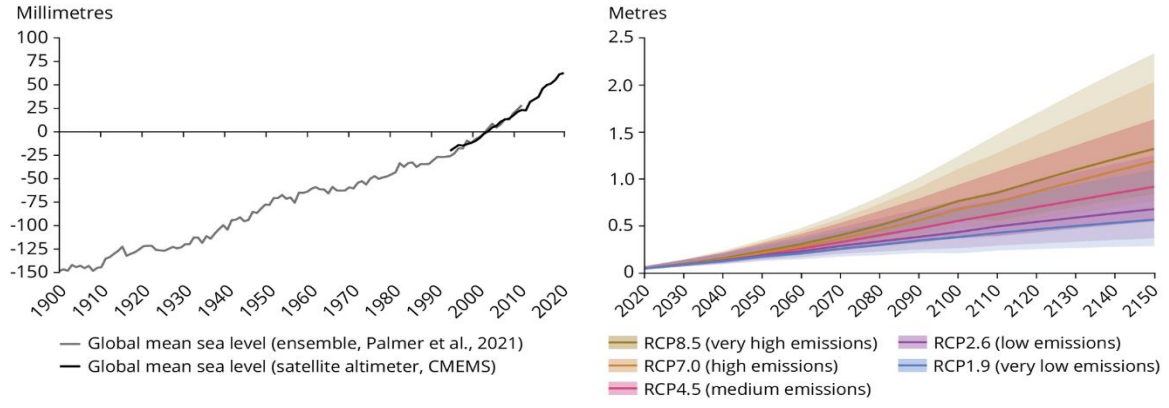


Figure 1: Taken from the The European Environment Agency (EEA) which is an agency of the European Union. It displays past global sea levels and forecasts future sea levels given some emission level.

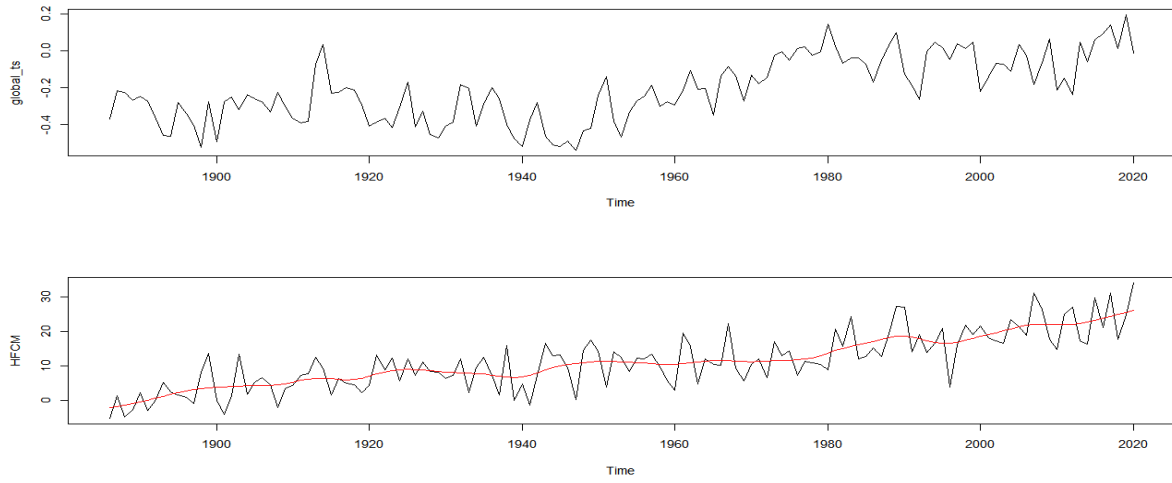


Figure 2: Plots side by side where the top plot is global mean temperature anomaly and bottom plot is long-term mean for sea level for Sweden, where the red line is a smoothed curve.

Table 1: ADF-test for HFCM

	statistic	1pct	5pct	10pct
tau3	-8.810	-3.990	-3.430	-3.130
phi3	38.790	8.430	6.490	5.470
tau2	-1.700	-3.460	-2.880	-2.570
phi1	2.160	6.520	4.630	3.810
tau1	0.170	-2.580	-1.950	-1.620

Table 2: ADF-test for HFCM first difference

	statistic	1pct	5pct	10pct
tau3	-10.220	-3.990	-3.430	-3.130
phi3	52.330	8.430	6.490	5.470
tau2	-10.270	-3.460	-2.880	-2.570
phi1	52.690	6.520	4.630	3.810
tau1	-10.140	-2.580	-1.950	-1.620

$$\begin{pmatrix} \Delta SeaLevel_t^1 \\ \Delta Temperature_t^2 \end{pmatrix} = + \begin{pmatrix} -3.0851*** \\ -0.0059 \end{pmatrix} ECT_{-1} + \begin{pmatrix} 1.3579*** & -4.3540 \\ 0.0052 & -0.8889*** \end{pmatrix} \begin{pmatrix} \Delta SeaLevel_{t-1}^1 \\ \Delta Temperature_{t-1}^2 \end{pmatrix} + \begin{pmatrix} 0.6851*** & -1.8202 \\ 0.0045 & -0.6737*** \end{pmatrix} \begin{pmatrix} \Delta SeaLevel_{t-2}^1 \\ \Delta Temperature_{t-2}^2 \end{pmatrix} + \begin{pmatrix} 0.2284* & -1.6210 \\ 0.0012 & -0.4477*** \end{pmatrix} \begin{pmatrix} \Delta SeaLevel_{t-3}^1 \\ \Delta Temperature_{t-3}^2 \end{pmatrix}$$

VECM model: first column in matrix is for sea level and second column is for temperature. Significance level is measured by 10-,5-, 1% which is represented by \*, \*\*, \*\*\* stars respectively.

Table 3: ADF-test for global temperature

	statistic	1pct	5pct	10pct
tau3	-3.200	-3.990	-3.430	-3.130
phi3	5.330	8.430	6.490	5.470
tau2	-1.570	-3.460	-2.880	-2.570
phi1	1.380	6.520	4.630	3.810
tau1	-1.340	-2.580	-1.950	-1.620

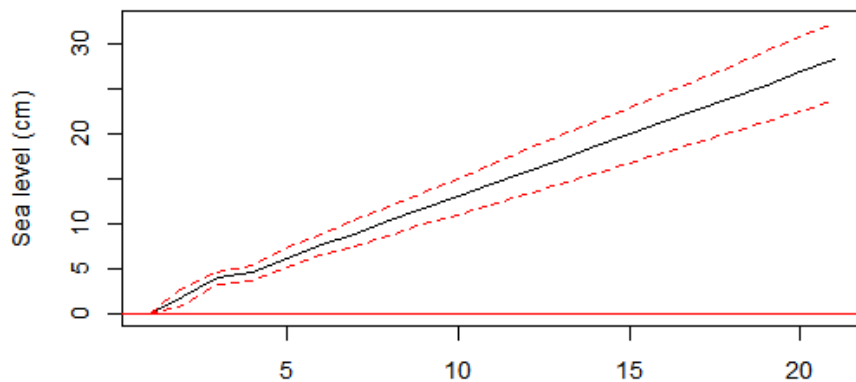
Table 4: ADF-test for global temperature first difference

	statistic	1pct	5pct	10pct
tau3	-10.900	-3.990	-3.430	-3.130
phi3	59.390	8.430	6.490	5.470
tau2	-10.900	-3.460	-2.880	-2.570
phi1	59.420	6.520	4.630	3.810
tau1	-10.920	-2.580	-1.950	-1.620

Table 5: Engle-Granger ADF-test

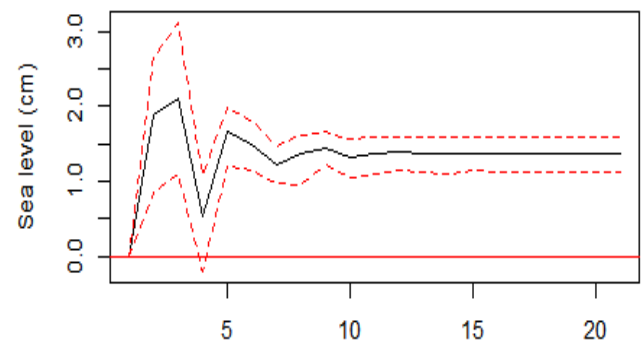
	statistic	1pct	5pct	10pct
tau3	-10.230	-3.990	-3.430	-3.130
phi3	52.390	8.430	6.490	5.470
tau2	-10.270	-3.460	-2.880	-2.570
phi1	52.760	6.520	4.630	3.810
tau1	-10.290	-2.580	-1.950	-1.620

Cumulative Orthogonal Impulse Response from Global temperature



95 % Bootstrap CI, 100 runs

Orthogonal Impulse Response from Global temperature



95 % Bootstrap CI, 100 runs

Figure 3 &amp; 4: Plots side by side where the left plot is cumulative irf and right plot is regular irf. Both are created using the VAR model created from our VECM model.

Forecasts from ARIMA(0,1,1) with drift

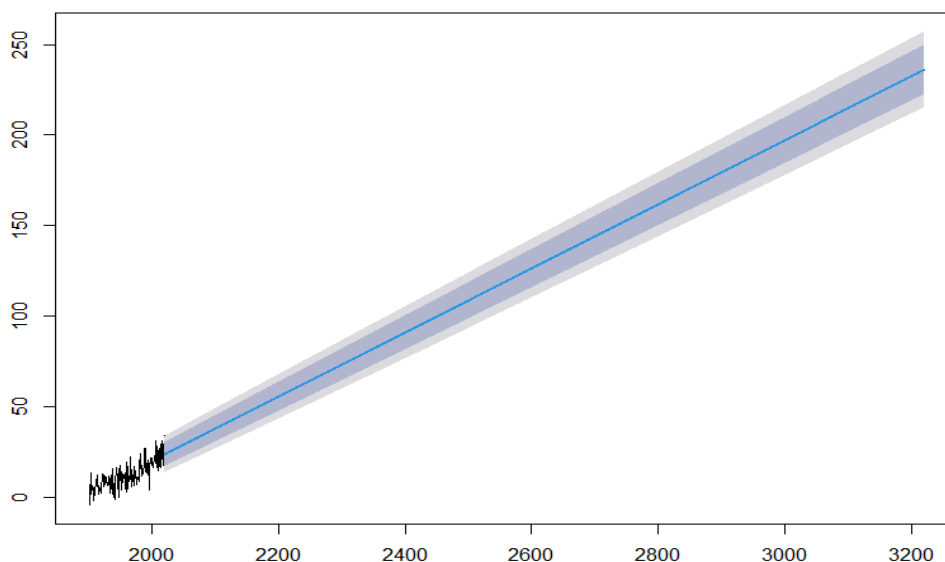


Figure 5: plot of forecast from an auto ARIMA model with sea level in (cm) on y-axis and time in years on x-axis.