# Absolute Sea Level Trend Forecasting via Ensemble Empirical Mode Decomposition Method

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## Introduction

Forecasting the sea level changes in response to climate change is a challenge for climate scientists. Accurate forecasting of absolute sea level trend (SLT) is also a main requirement in coastal management. Traditionally, tidal harmonic analysis at the location of tide gauge (TG) stations has been used for the prediction. However, this method ignores the hydrometeorology influences lead to high forecasting errors. In addition, sea level trend has certain periodicity and fluctuation that can be restored and used as internal information for forecasting.

The present study investigated the combined use of quantitative forecasting methods for absolute sea level (or Dynamic Topography, DT) using empirical mode decomposition (EMD) and discrete wavelet transform (DWT) as inputs of autoregressive integrated as well as neural network models for DT data over 24 years. Apart from TG data, Satellite altimetry (SA) which provides high spatial resolution of sea level data have been used for the DT forecasting in Baltic Sea. The SA data are compiled by nine SA missions during 1995 to 2019 over the entire sea. This methodology also requires the utilization of high-resolution geoid models to maximize the opportunities in deriving realistic DT using SA data. Also, careful spatial data selection and outliers' removal using data screening is a prerequisite.

| ID | TG Station | | Latitude [°] | Longitude [°] |
|---|---|---|---|---|
| 1 | Helsinki | (FI) | 60.15363 | 24.95622 |
| 2 | Hamina | (FI) | 60.56277 | 27.1792 |
| 3 | Hanko | (FI) | 59.82287 | 22.97658 |
| 4 | Pietarsaari | (FI) | 63.70857 | 22.68958 |
| 5 | Kaskinen | (FI) | 62.34395 | 21.21483 |
| 6 | Rauma | (FI) | 61.13353 | 21.42582 |
| 7 | Oulu | (FI) | 65.0403 | 25.4182 |
| 8 | Spikarna | (SW) | 62.3633 | 17.5311 |
| 9 | Marviken | (SW) | 58.5536 | 16.8372 |
| 10 | Simrishamn | (SW) | 55.5575 | 14.3578 |
| 11 | Forsmark | (SW) | 60.4086 | 18.2108 |
| 12 | Furuögrund | (SW) | 64.9158 | 21.2306 |

**Table 1.** TG stations list

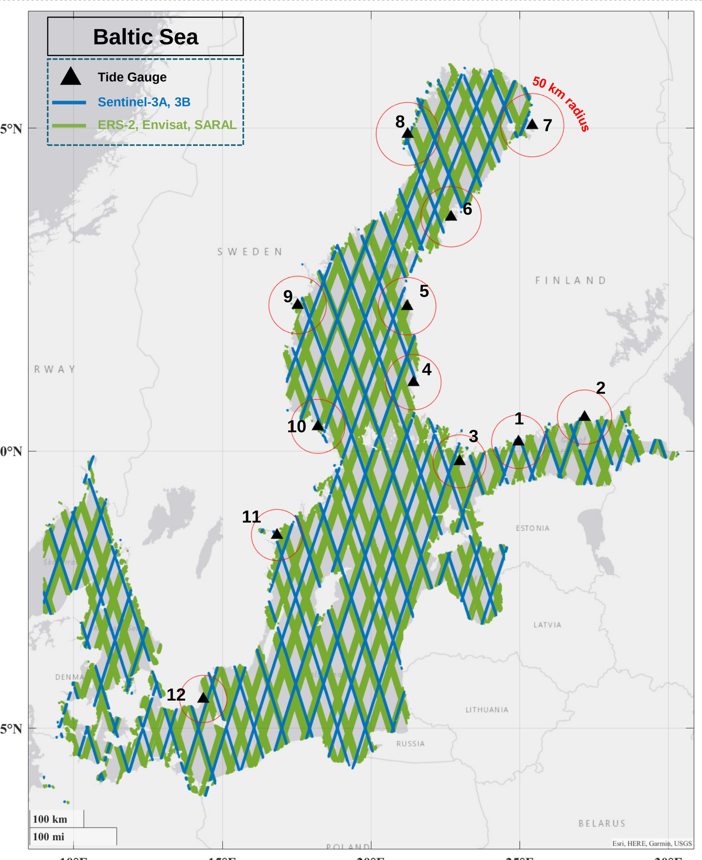



**Fig 1.** Location of TG stations and SA passes in BS

## Datasets

**TG:** 12 TG stations data in Baltic Sea (Table 1)
**SA:** Sentinel-3A (S3A), Sentinel-3B (S3B), SARAL (SRA), Envisat (ENV), ERS-2 (ER2) data during 1995-2019 using ALES+ retracker (Baltic+SEAL)
**Model:** NKG2015 Geoid & NKG2016LU Land Uplift

## Objectives

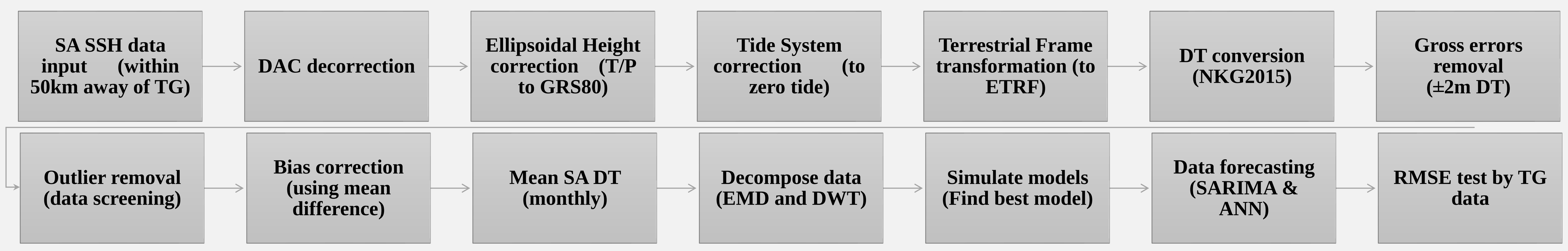
- ❑ Decompose Sea Level data using EMD and DWT transformation.
- ❑ Sea Level forecasting by decomposed SA data and using most robust model in the Baltic Sea.

## Methodology

1. Spatial selection and outlier detection: extract SA data within 50km from TG and screen out low-quality data using data screening. Vertical land movement (VLM) correction for TG time series.
2. Monthly average of SA DT of each mission at near each TG considered as $DT_{SA}$.
3. Test $DT_{SA}$ data stationary using Augmented Dickey-Fuller test. Also, transforming data to 1) detrended: reduce 1st degree polynomial trend of $DT_{SA}$, 2) difference: differences between adjacent elements of detrended $DT_{SA}$
4. Decompose $DT_{SA}$ using EMD () and DWT ()
5. SA DT time series forecasting for 2 years using different models including: Autoregression (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving-Average (SARIMA).
6. Assess model adequacy using Akaike information criteria (AIC) and Bayesian (Schwarz) information criteria (BIC) to select the most robust model also using statistical evaluation criteria, including the correlation coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^o - y_i^r)}$$

n: number of data
$y^o$: observed $DT_{TG}$
$y^r$: forecast $DT_{SA}$



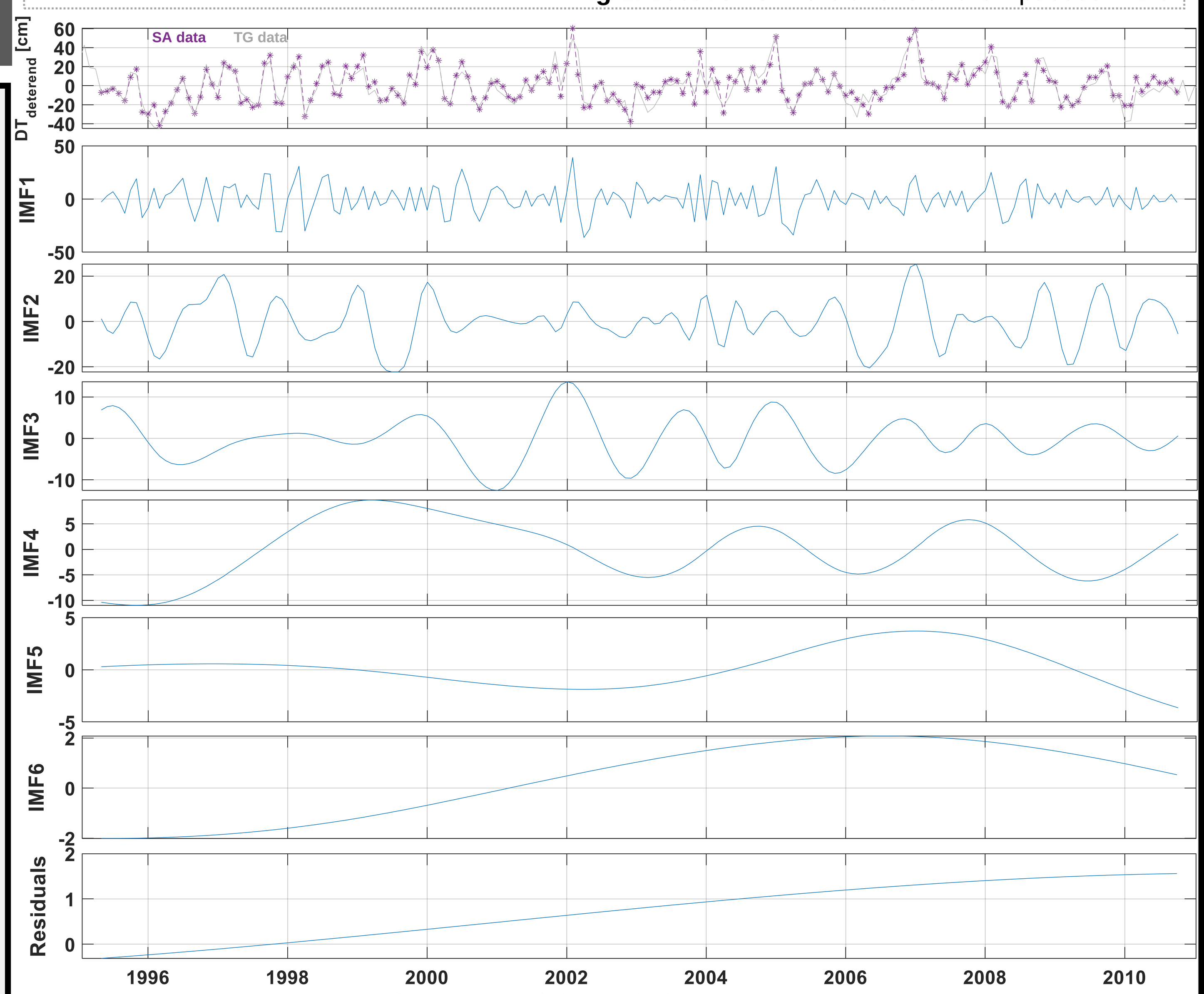




**Fig 2.** EMD of detrended $DT_{SA}$ at TG#1

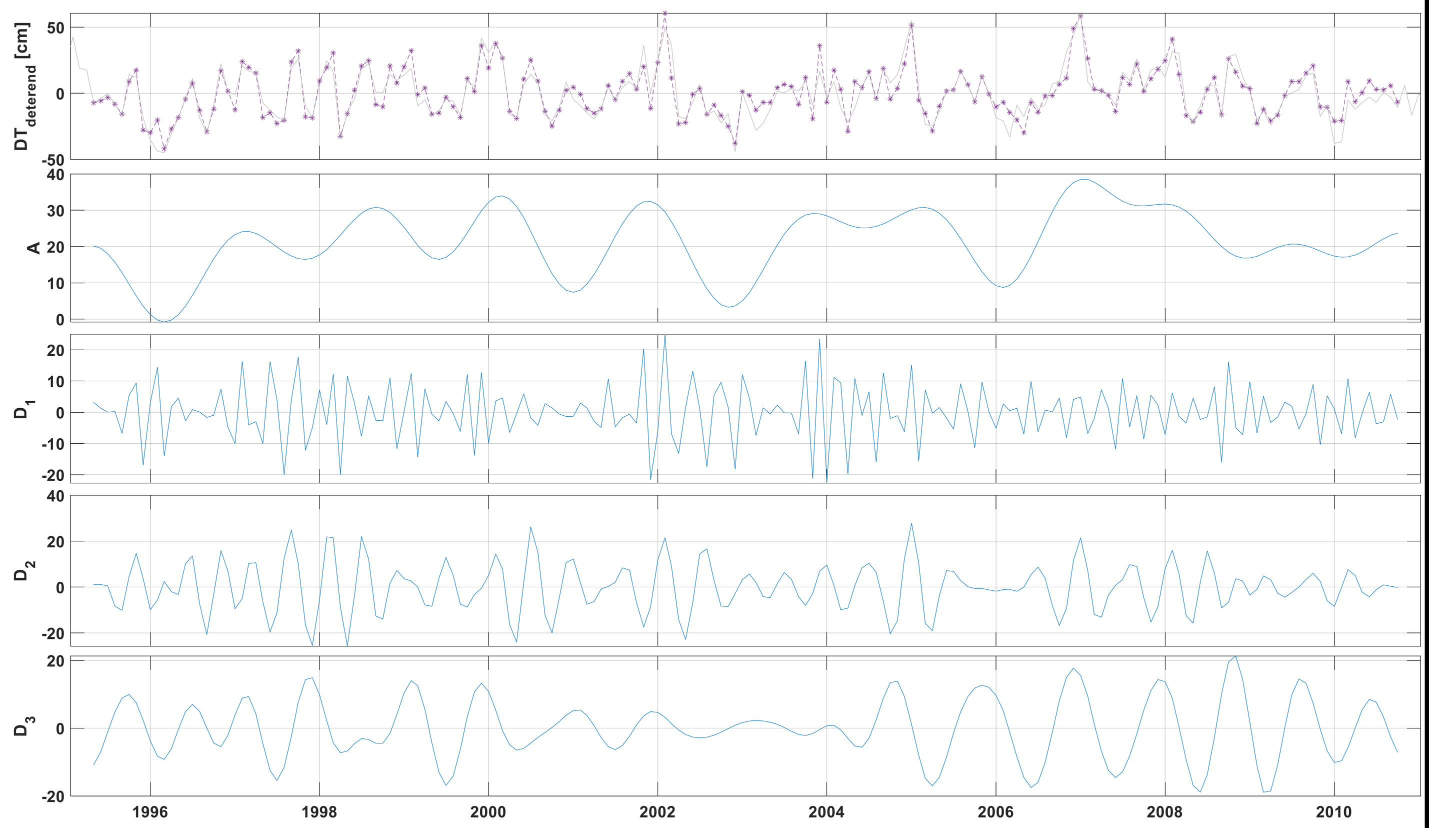


**Fig 3.** DWT of detrended $DT_{SA}$ at TG#1

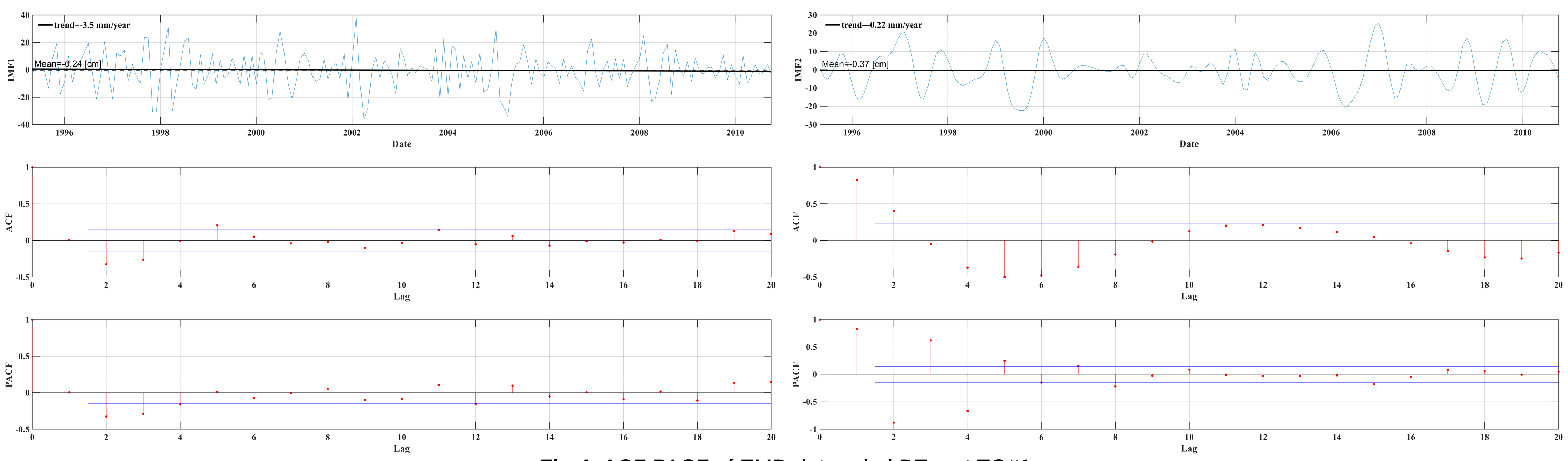


**Fig 4.** ACF PACF of EMD detrended $DT_{SA}$ at TG#1

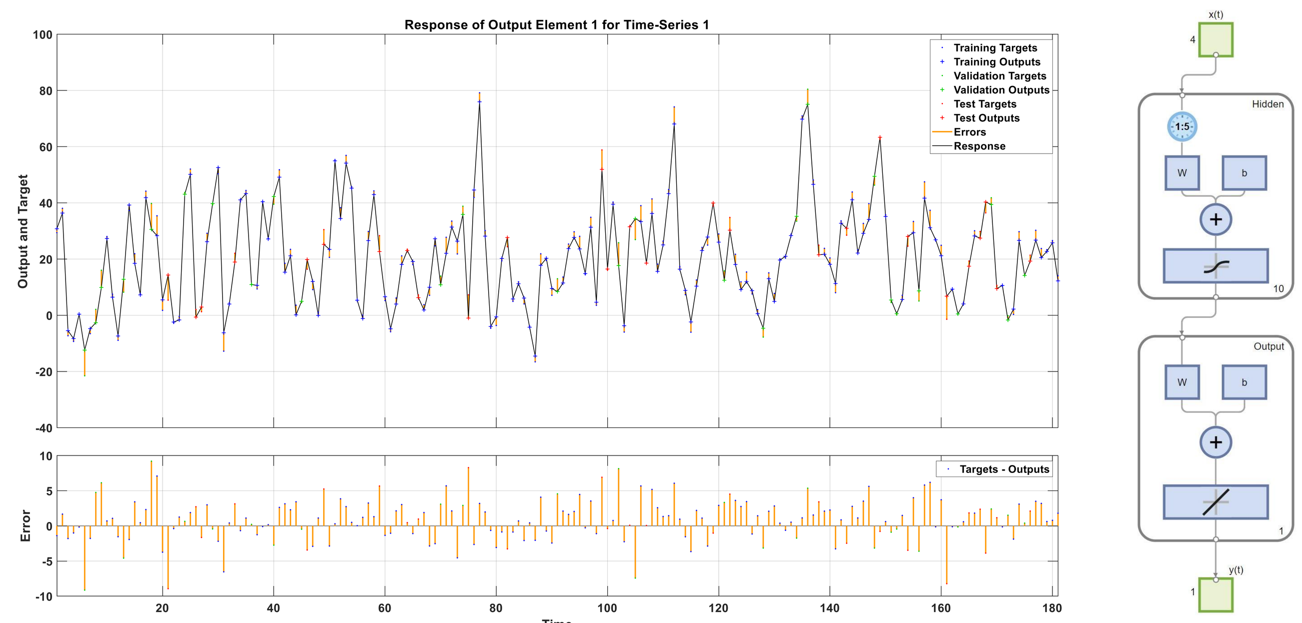


**Fig 5.** ANN performance results and structure for training, test and validation sets

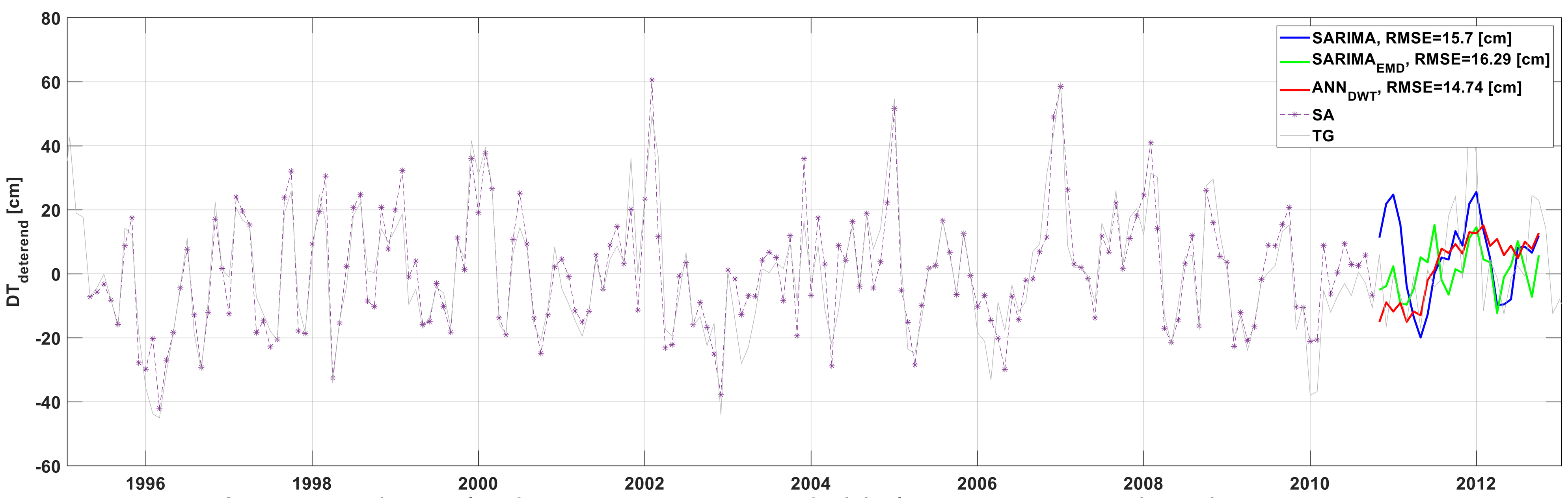



**Fig 8.** Forecasting results of $DT_{SA}$ at TG#1: SARIMA of original $DT_{SA}$, EMD $DT_{SA}$ and ANN by DWT $DT_{SA}$

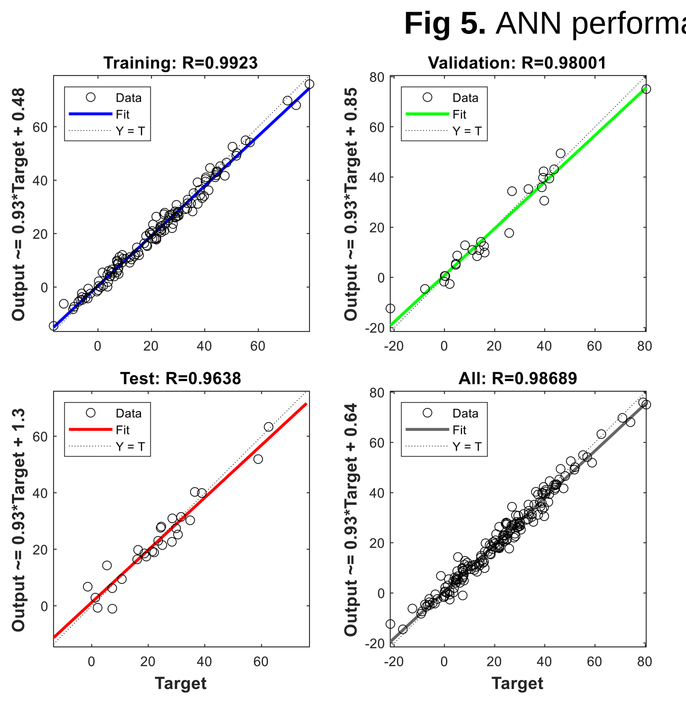



**Fig 6.** SARIMA models of $DT_{SA}$ at TG#1 by two

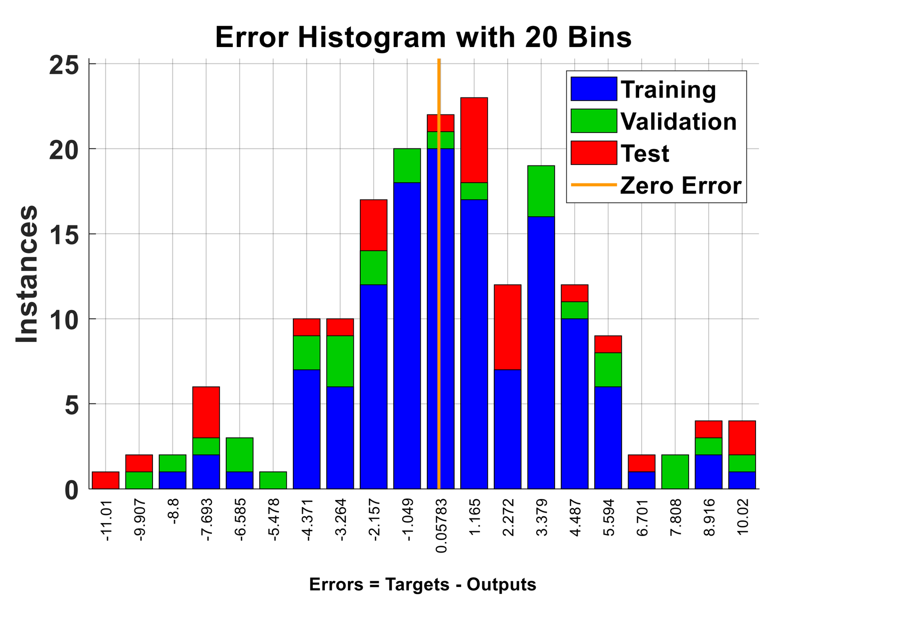



**Fig 7.** SARIMA models of $DT_{SA}$ at TG#1 by two

## Results

- ► Good agreement is obtainable using SARIMA by ARIMA(4,0,1) SAR(48) SMA (12) with 12 month Seasonality model for $DT_{SA}$ forecasting (Figure 3 and 5).
- ► DT data need to be detrended to consider for Sea Level Trend before forecasting (Figure 4).
- ► DT forecasting can be forecasted by ~15 cm RMSE using SA data for 2 years. This forecasted data can be served for 2 years data gap of SA data (during 2011-2013).

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