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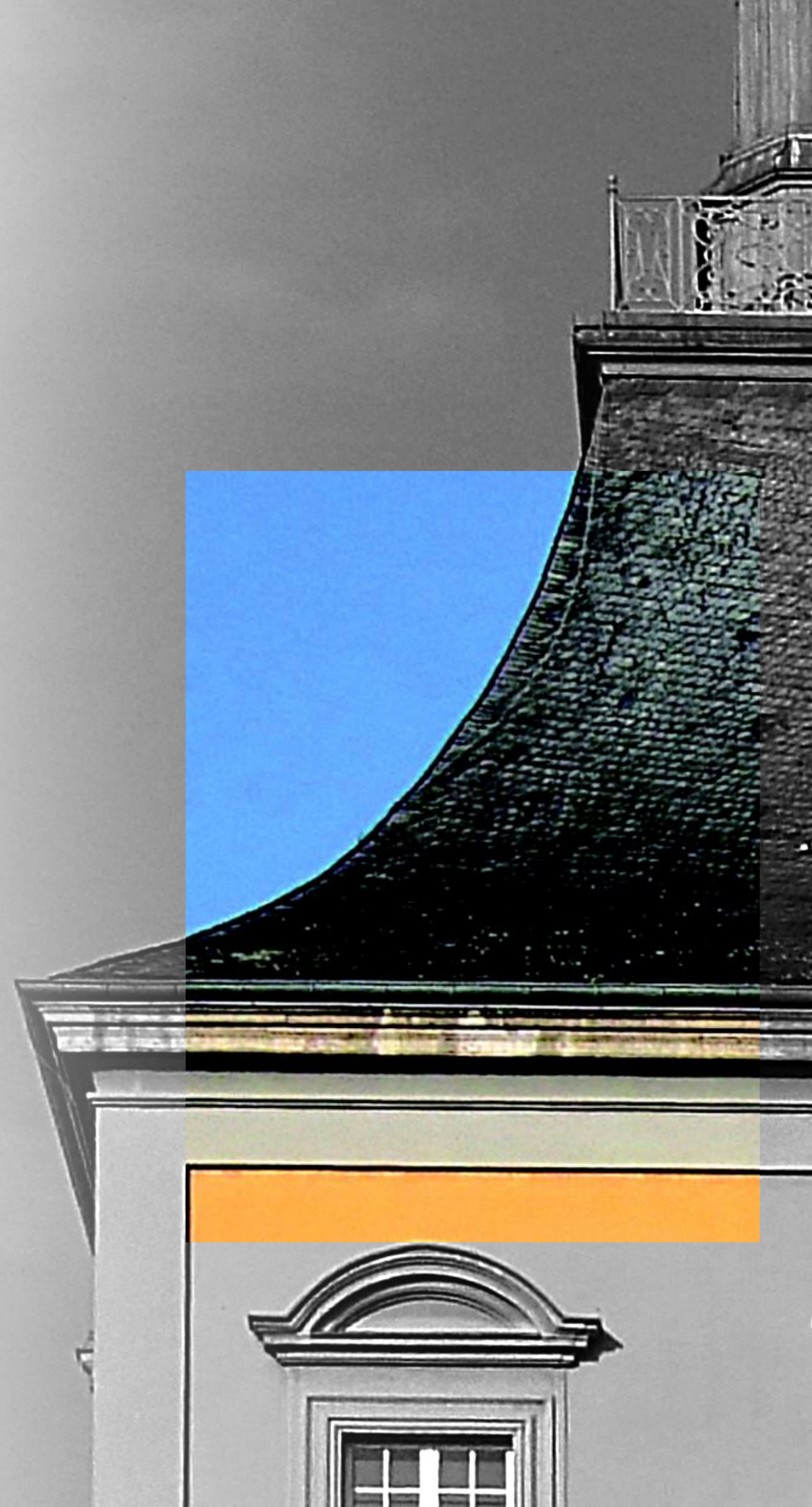
EGU2020: SHARING GEOSCIENCE ONLINE

HOW UNCERTAIN IS THE HYDROLOGICAL CONTRIBUTION TO GLOBAL SEA LEVEL BASED ON HYDROLOGICAL MODELLING COMPARED TO OBSERVATIONAL DATA?



Christian Mielke[1], Olga Engels[1], Bernd Uebbing[1], Helena Gerdener[1], Lara Börger[1], Kerstin Schulze[1], Petra Döll[2], Jürgen Kusche[1]

[1]Institute of Geodesy and Geoinformation, Bonn University, Bonn, Germany
[2]Institute of Physical Geography, Goethe University Frankfurt, Frankfurt am Main, Germany

ABSTRACT

Our main questions:

What is the contribution of global terrestrial hydrology to sea level rise, what is its uncertainty from modelling, to what extent is the trend time variable, and how do different methods differ in their trend and acceleration estimates?

Our main result:

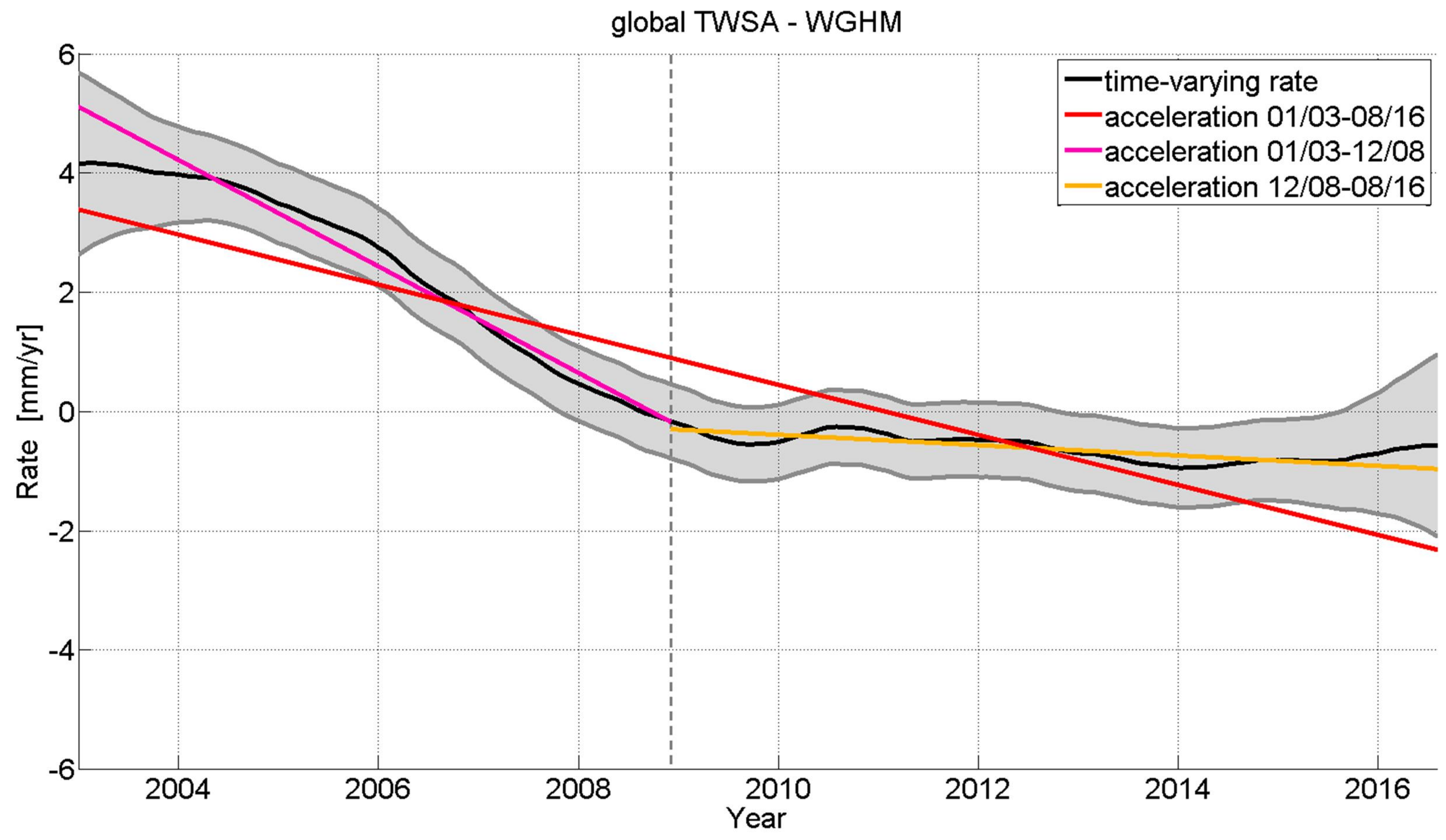
1. Contribution of global terrestrial hydrology to sea level rise between model and observations agrees within 1σ for Dec. 2008 – Aug. 2016
2. For Jan. 2003 – Aug. 2016 contribution of global terrestrial hydrology to sea level rise from observations is negative and agrees within 2σ, while model shows positive trend
3. Analysis of generated ensemble shows large uncertainties in modelling (mostly in groundwater compartment)
4. Changes in the derived time-varying trends represent accelerations, which are not constant over the time period Jan. 2003 – Aug. 2016

MOTIVATION

- Individual contributors to global and regional mean sea level along with corresponding uncertainties is crucial for future projections
- ➢ Contribution of terrestrial hydrology seems to be the least known / the most uncertain

We analyse:

- 3 different (model- and observation-based) datasets
- using 2 different approaches for time series analysis
- to estimate rates, accelerations and corresponding uncertainties of the land water storage anomalies



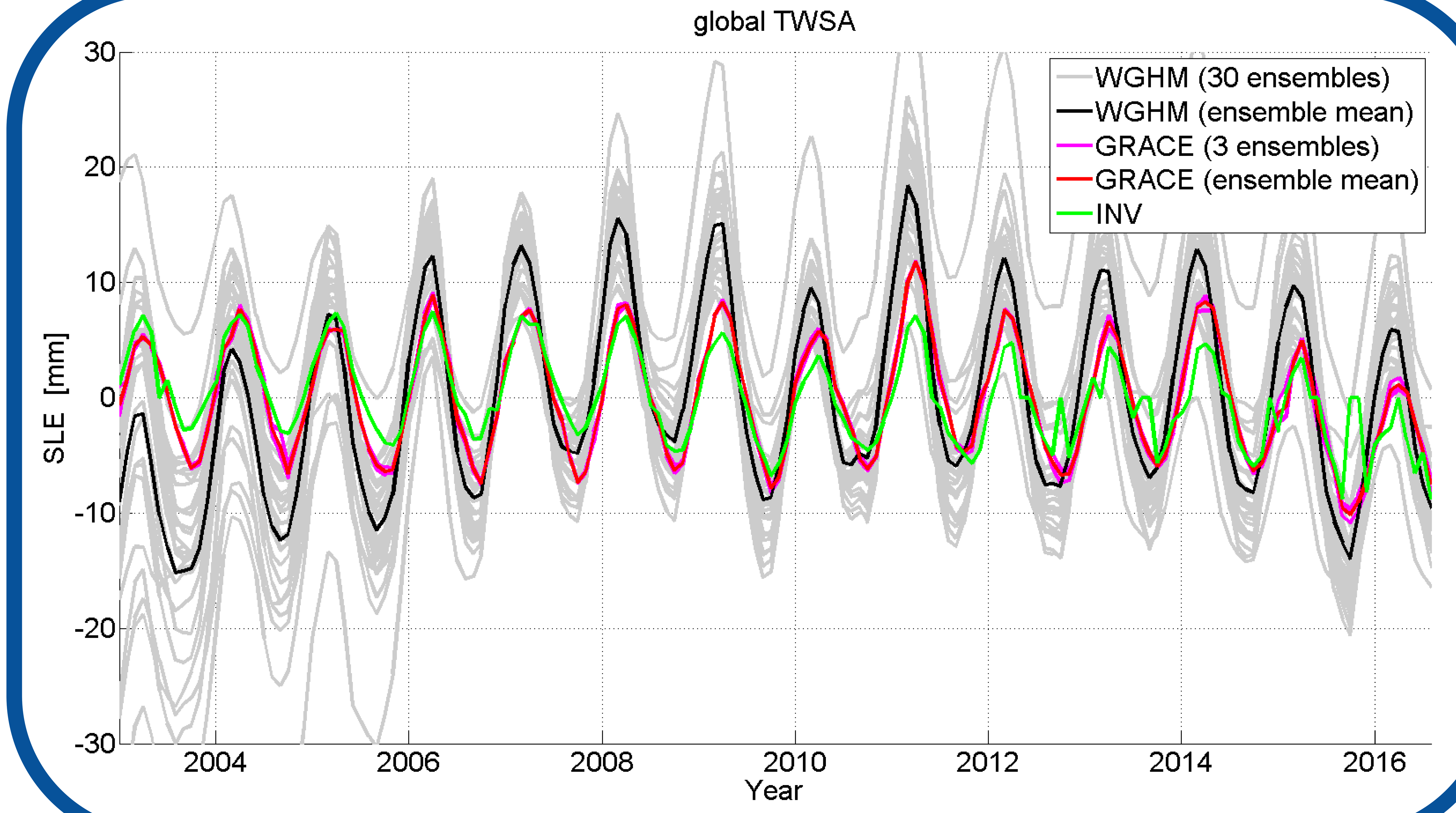
DATA

WaterGAP Global Hydrological Model 2.2d (WGHM) [1]

- 10 Storages: canopy, global lake, global wetland, groundwater, local lake, local wetland, reservoir, river, snow, soil
- Müller Schmied et al. (2016)
- 30 ensembles (to account for model uncertainties)

GRACE Level-3 Monthly Solutions

- Ensemble of ITSG2018, GFZ RL06 and CSR RL06 Level-2 Data up to d/o 96
- Post-processing[2]: corrected for deg1, C20, GIA, filtered using DDK3, earthquake correction



Joint inversion using GRACE and altimetry data (INV)

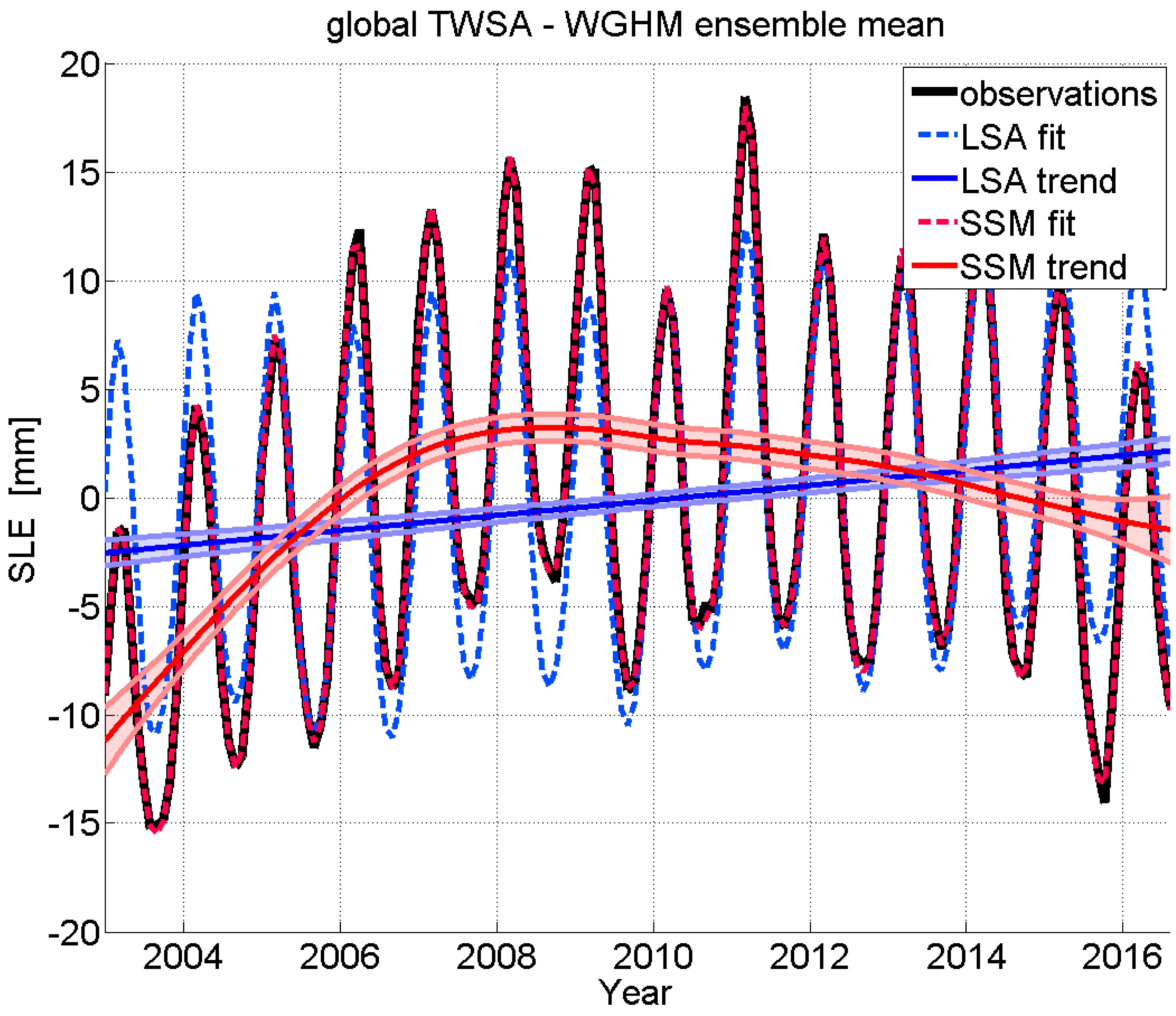
- Updated version from Uebbing et al. (2019)
- Joint processing of GRACE-RL06 and Jason-1/-2 along-track altimetry data
- Fitting of time variable scaling factors to time invariant, pre-defined patterns (fingerprints)

[1]Introduction: https://en.wikipedia.org/wiki/WaterGAP
[2]Data processing: https://www.apmg.uni-bonn.de/daten-und-modelle/grace-monthly-solutions

METHODOLOGY - TIME SERIES ANALYSIS

We perform:

- Deterministic approach: Usually used Least-Squares Adjustment (LSA)
- Stochastic approach: State Space Model (SSM, Durbin and Koopman, 2012)
- Based on global Total terrestrial Water Storage Anomalies = global TWSA (Jan. 2003 – Aug. 2016)
- Note: All terrestrial cells are used, except Greenland and Antarctica, i.e. signal over glaciated areas is **not** separated



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STATE SPACE MODEL = SSM

Observation equation

$$y_t = Z_t \alpha_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, H)$$

State equation

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \qquad \eta_t \sim N(0, Q)$$

Observation noise

$$H = I \sigma_\varepsilon^2$$

State vector

$$\alpha_t = [\text{trend} \quad \text{harm. terms}]^T$$

Process noise

$$Q = \text{diag}(\sigma_{\text{trend}}^2 \quad \sigma_{\text{harm.terms}}^2)$$

Harmonic terms

Trend (integrated random walk)

Following Harvey (1989) for defining the trend and harmonic terms recursively:

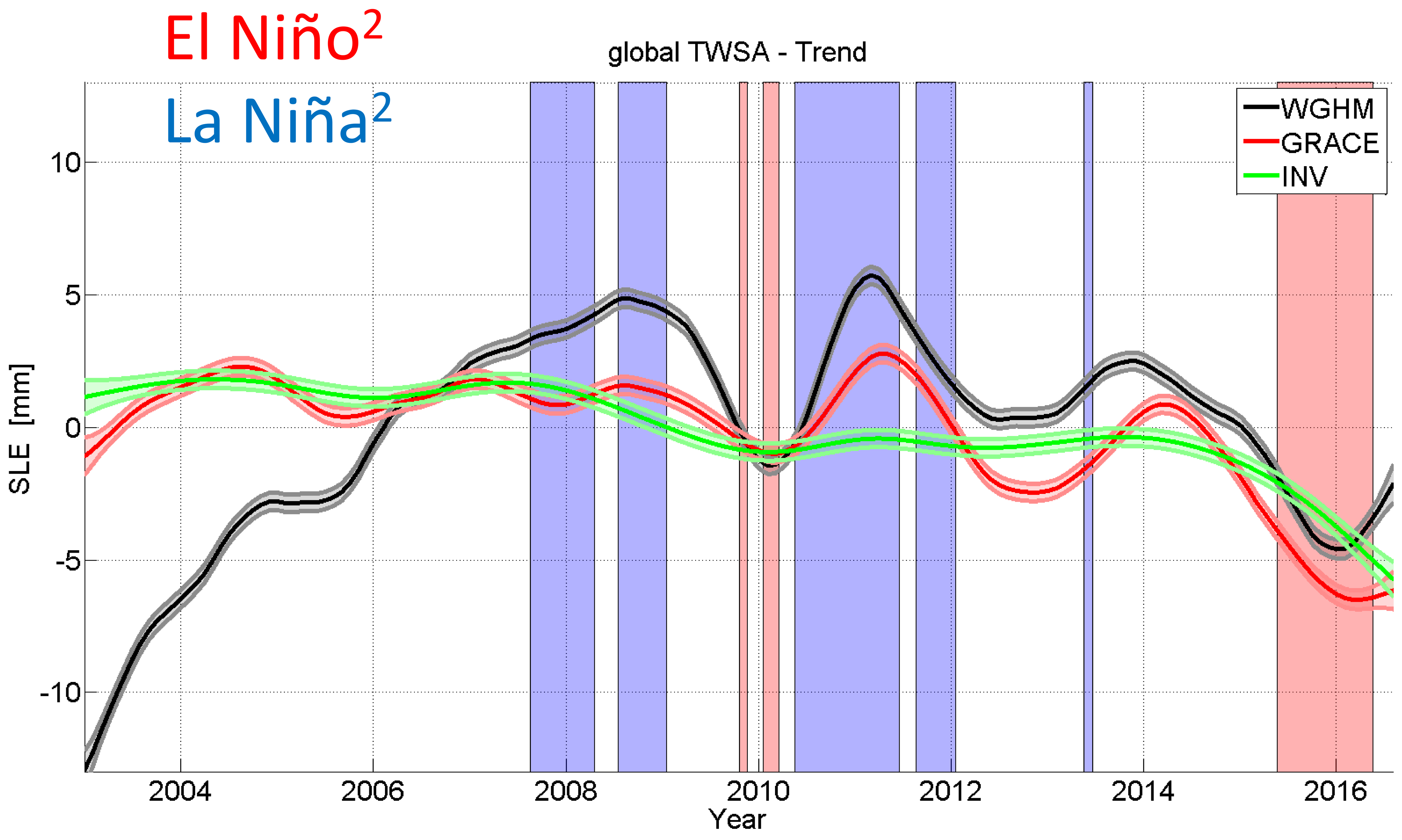
$$c_t = c_{t-1} \cos\omega + s_{t-1} \sin\omega + \varsigma_t$$
$$s_t = -c_{t-1} \sin\omega + s_{t-1} \cos\omega + \varsigma_t \qquad \varsigma_t \sim N(0, \sigma_{\text{harm.terms}}^2)$$

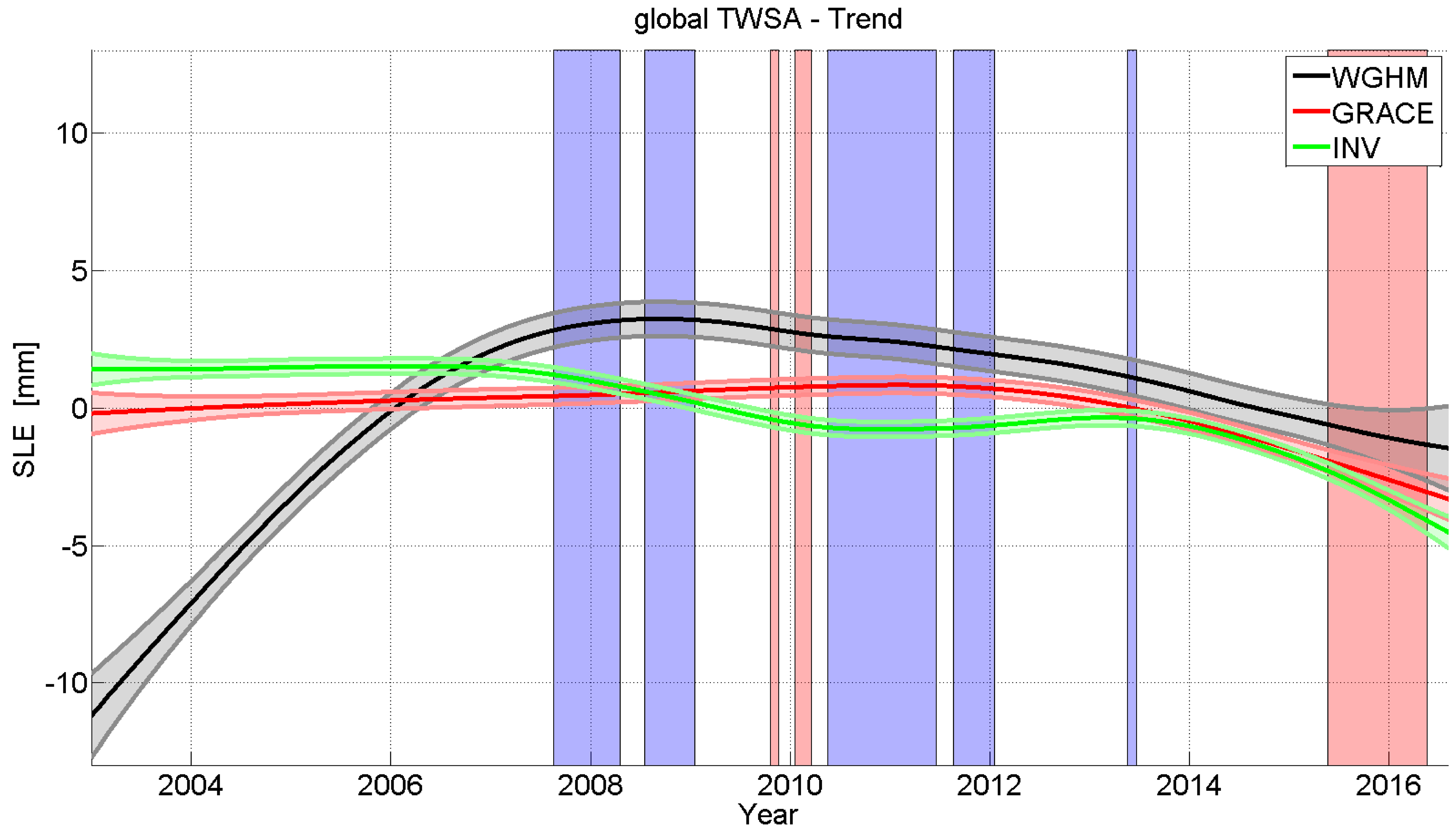
$$\mu_{t+1} = \mu_t + \beta_t + \xi_t \qquad \xi_t = 0$$
$$\beta_{t+1} = \beta_t + \zeta_t \qquad \zeta_t \sim N(0, \sigma_{\text{trend}}^2)$$

Kalman Filter

Estimation of noise parameters follows Durbin and Koopman (2012) and Didova et al. (2016)

RELATION BETWEEN THE TIME-VARYING TREND AND ENSO[1]





Estimating only annual, semi-annual and ca. 0.6 years[3] periodic signal
→ Long-term signal of all data sets strongly related with ENSO events

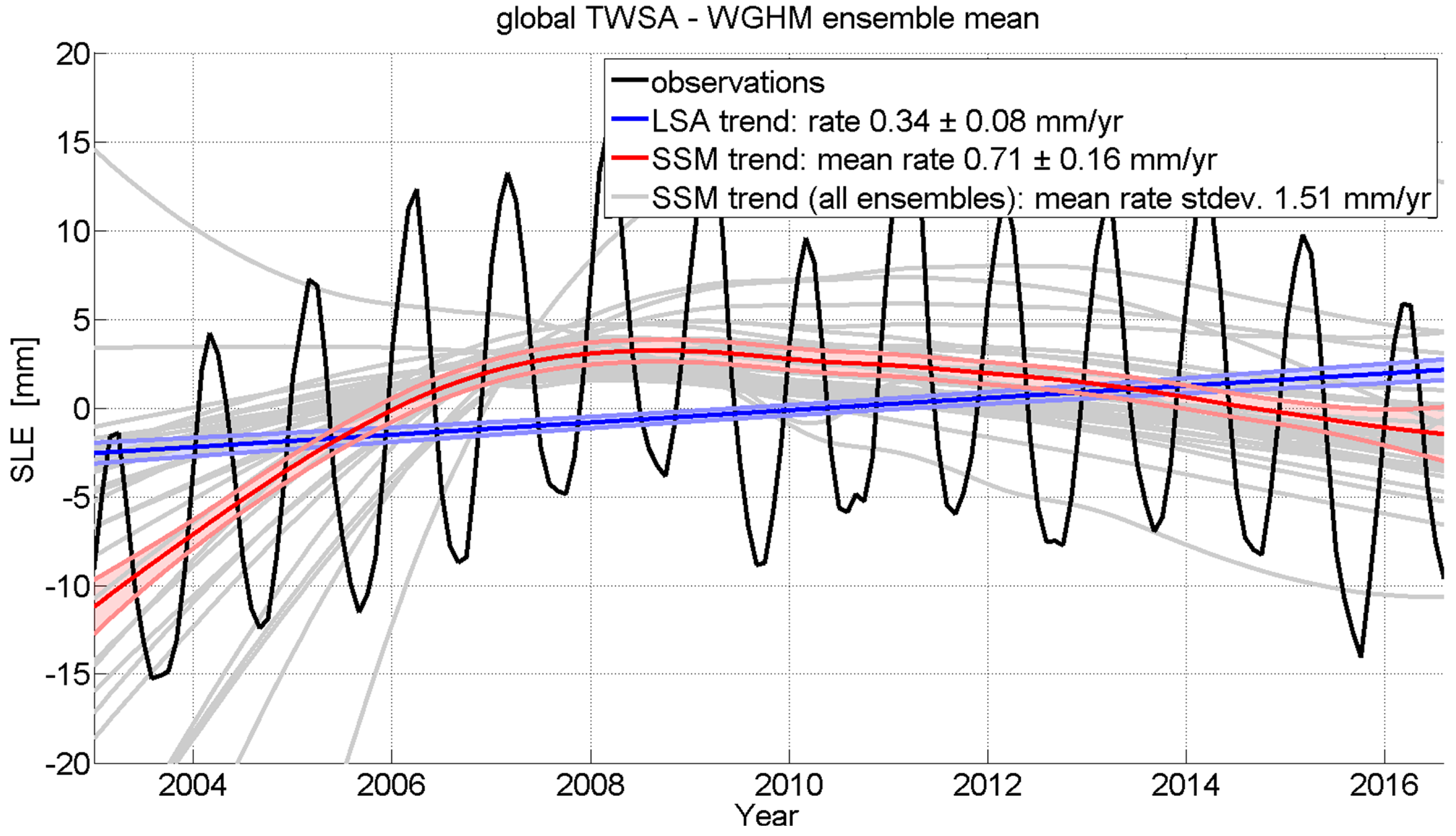
Additional estimation of a long periodic signal (ca. 3.4 years [3]) that is present in all three time series
→ The estimated rate is freed from interannual variations mostly related to ENSO

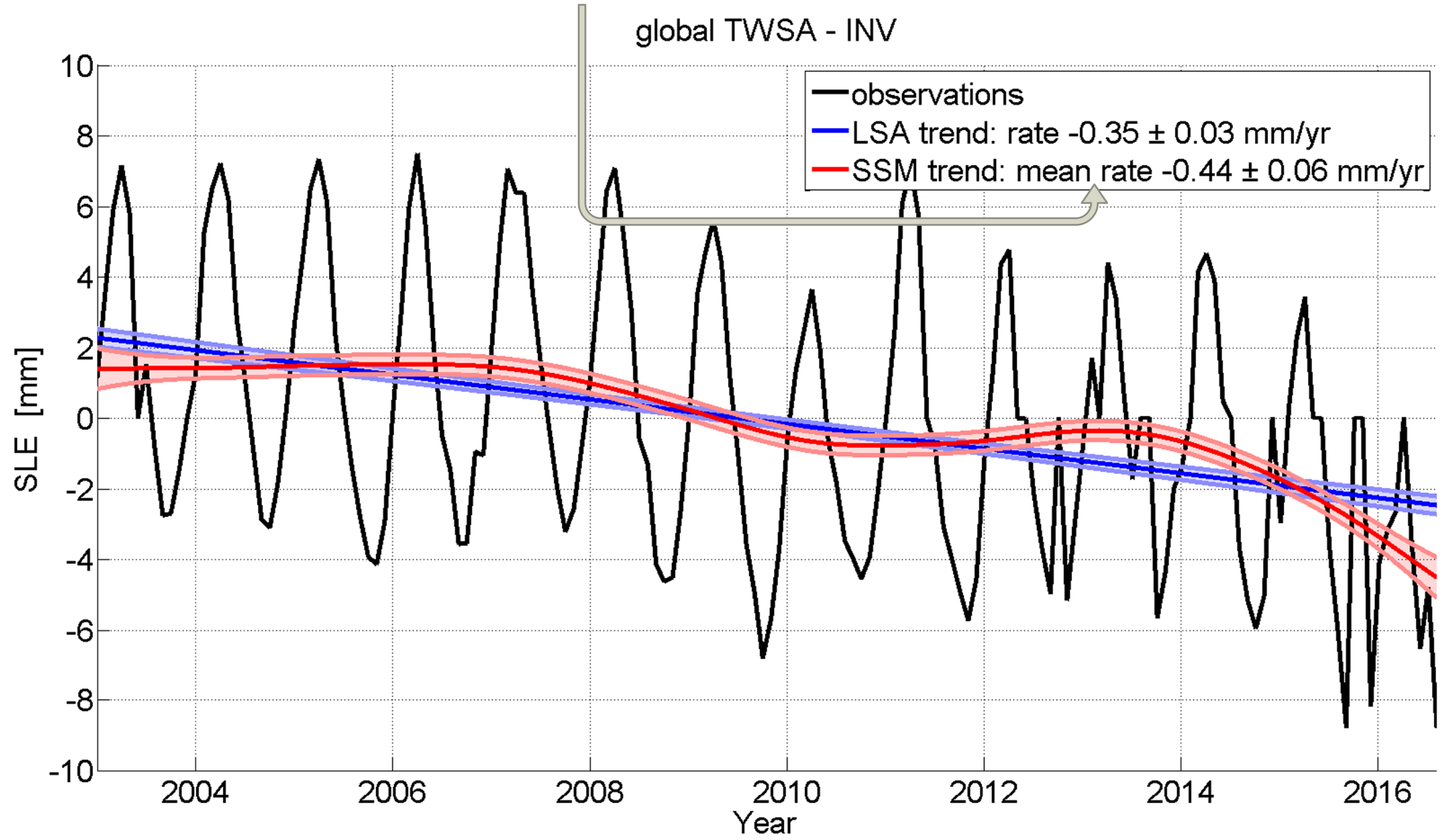
[1]ENSO = El Niño-Southern Oscillation
[2]based on Multivariate ENSO Index Version (MEI.v2), threshold: +/- 1.0: https://www.psl.noaa.gov/enso/mei/
[3]based on spectral analysis

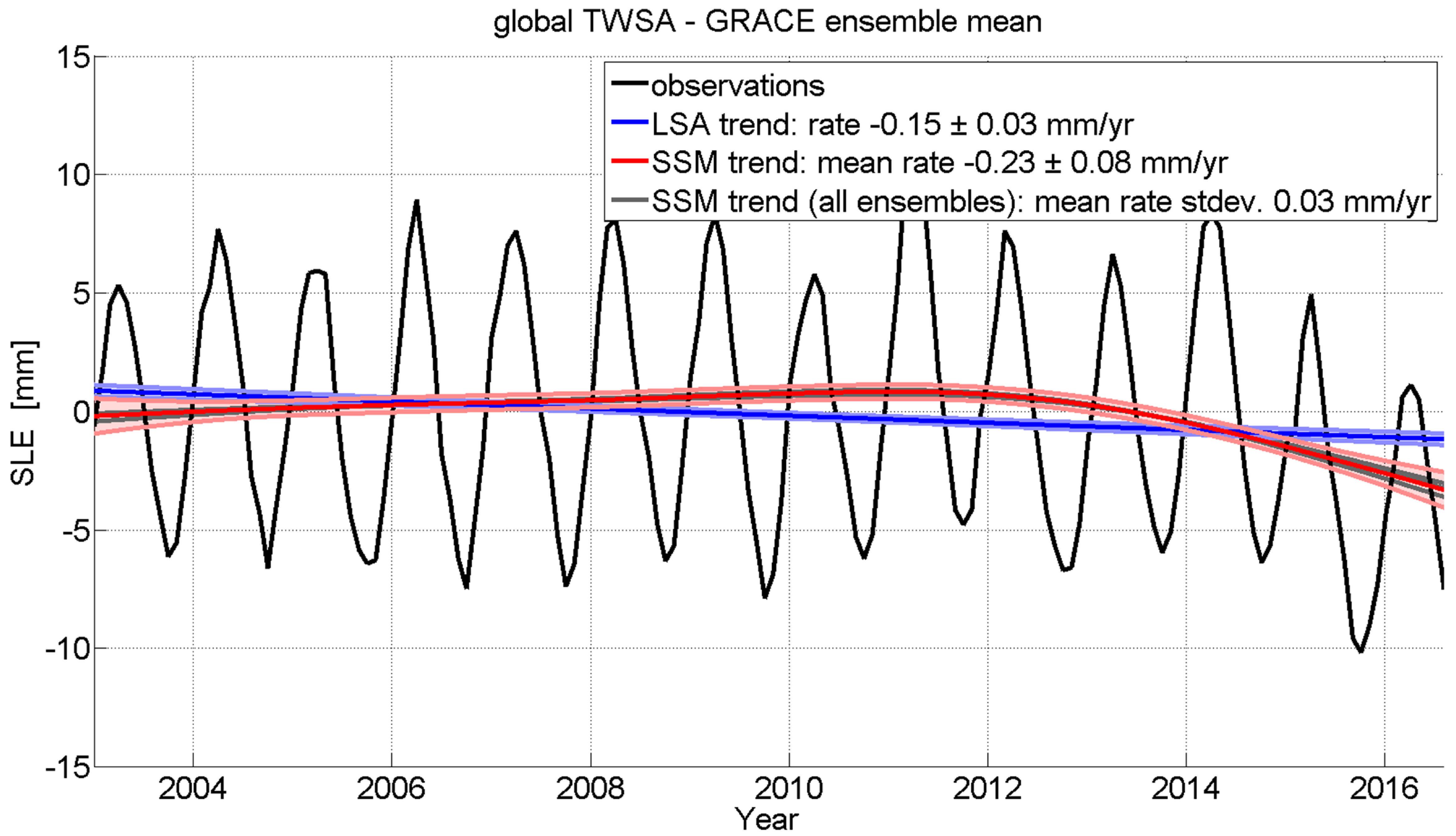
RESULTS – TIME SERIES ANALYSIS

- LSA- and SSM- rates agree within 2σ
- WGHM – stdev.: LSA < SSM < Spread
- GRACE – stdev.: LSA = Spread < SSM
- WGHM: Stdev. of LSA and SSM too optimistic compared to spread of ensembles
- **But:** Standard deviation from spread of only 3 (for GRACE) or 30 (for WGHM) ensembles realistic?

stdev. = standard deviation; mean rate = temporal mean

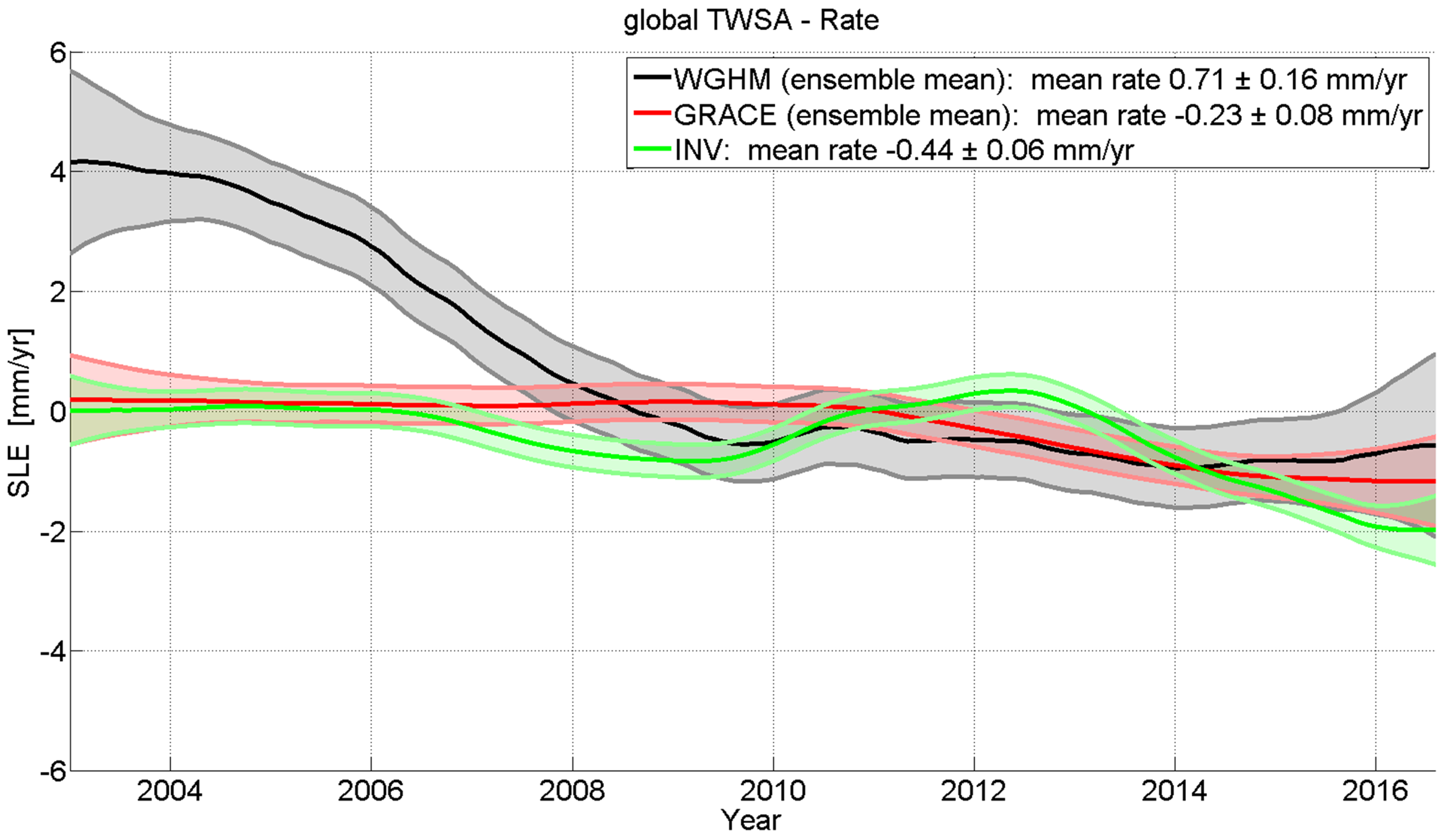






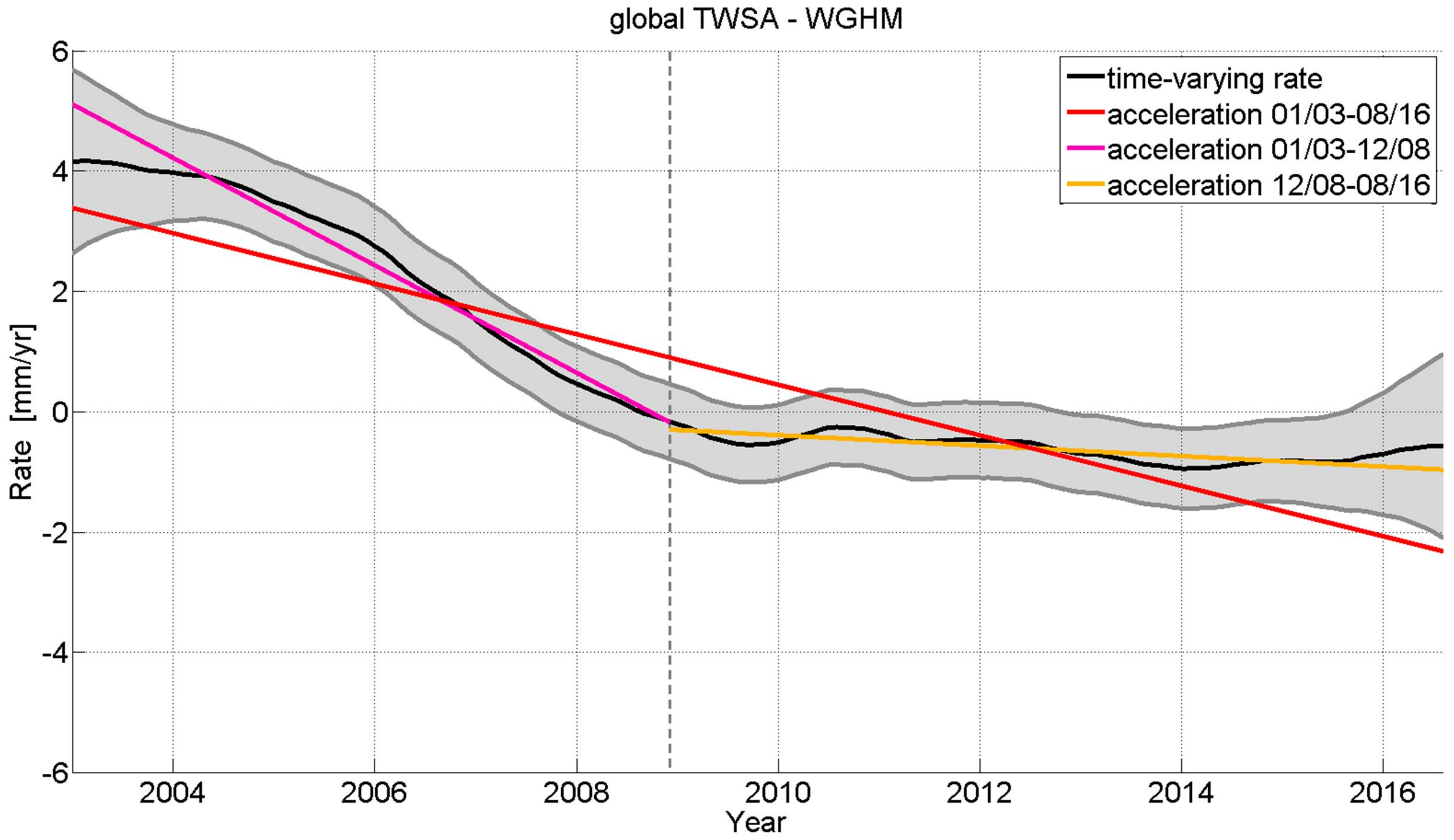
RESULTS – TIME SERIES ANALYSIS

- SSM allows more insights than LSA when validating different time series
- GRACE & INV: Negative rate
  → Ocean mass increase
- WGHM: Positive rate
  → WGHM ↯ INV & GRACE
- Possible explanation: Glaciers are treated as non-glaciated areas in WGHM
- Considering different time periods provide different results → Next slide



RESULTS – TIME SERIES ANALYSIS

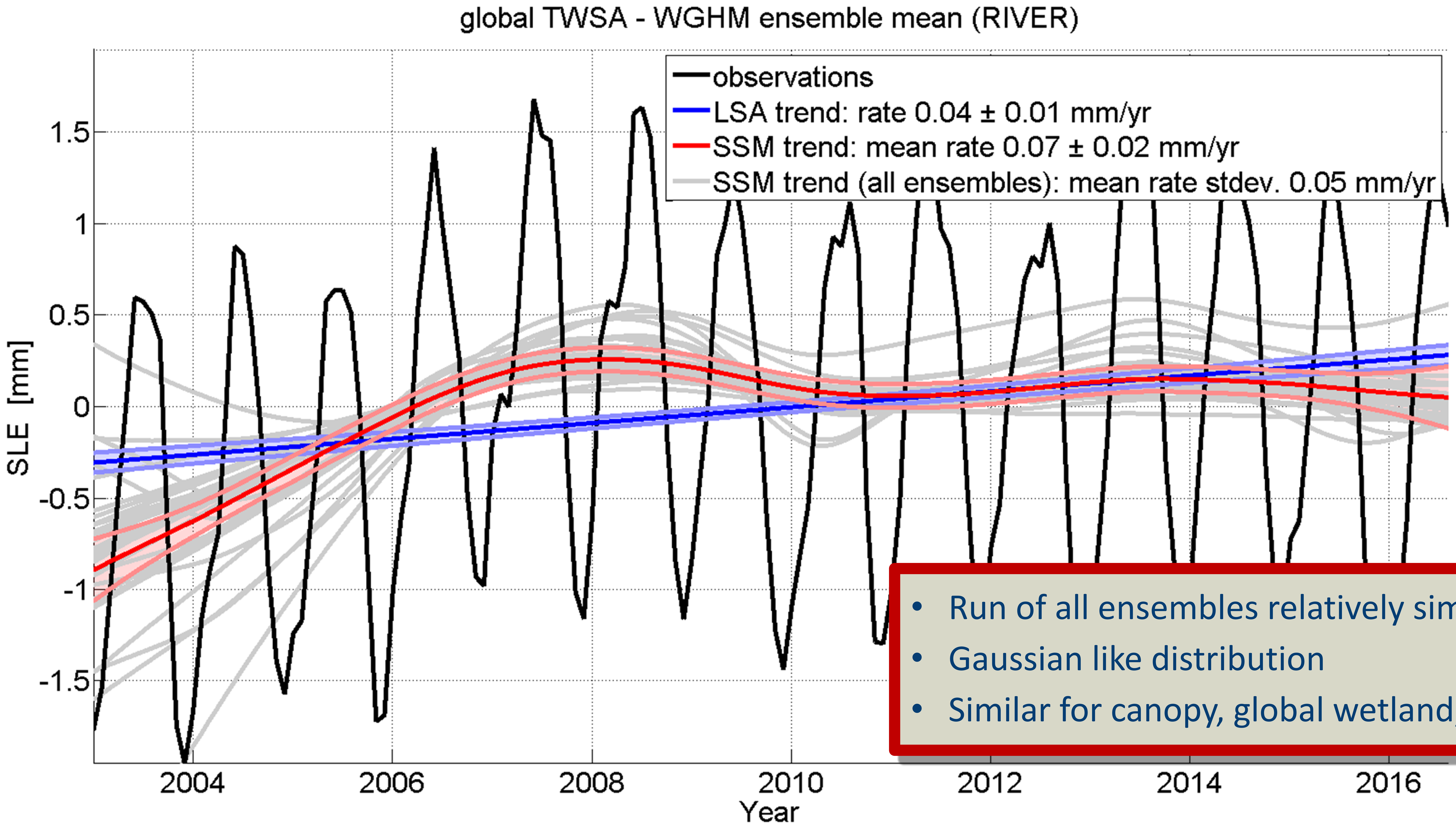
- Change in rate = acceleration
- No constant acceleration over the considered time period
- Jan. 2003 – Dec. 2008: Significant[1] difference between SSM mean rate of WGHM and GRACE & INV explainable by individual compartments?
- Jan. 2003 – Dec. 2008: Significant negative acceleration of WGHM rate
- Dec. 2008 – Aug. 2016: No significant acceleration of WGHM rate → Rates of WGHM, GRACE and INV agree within 1σ
- GRACE & INV: No significant acceleration over different time periods

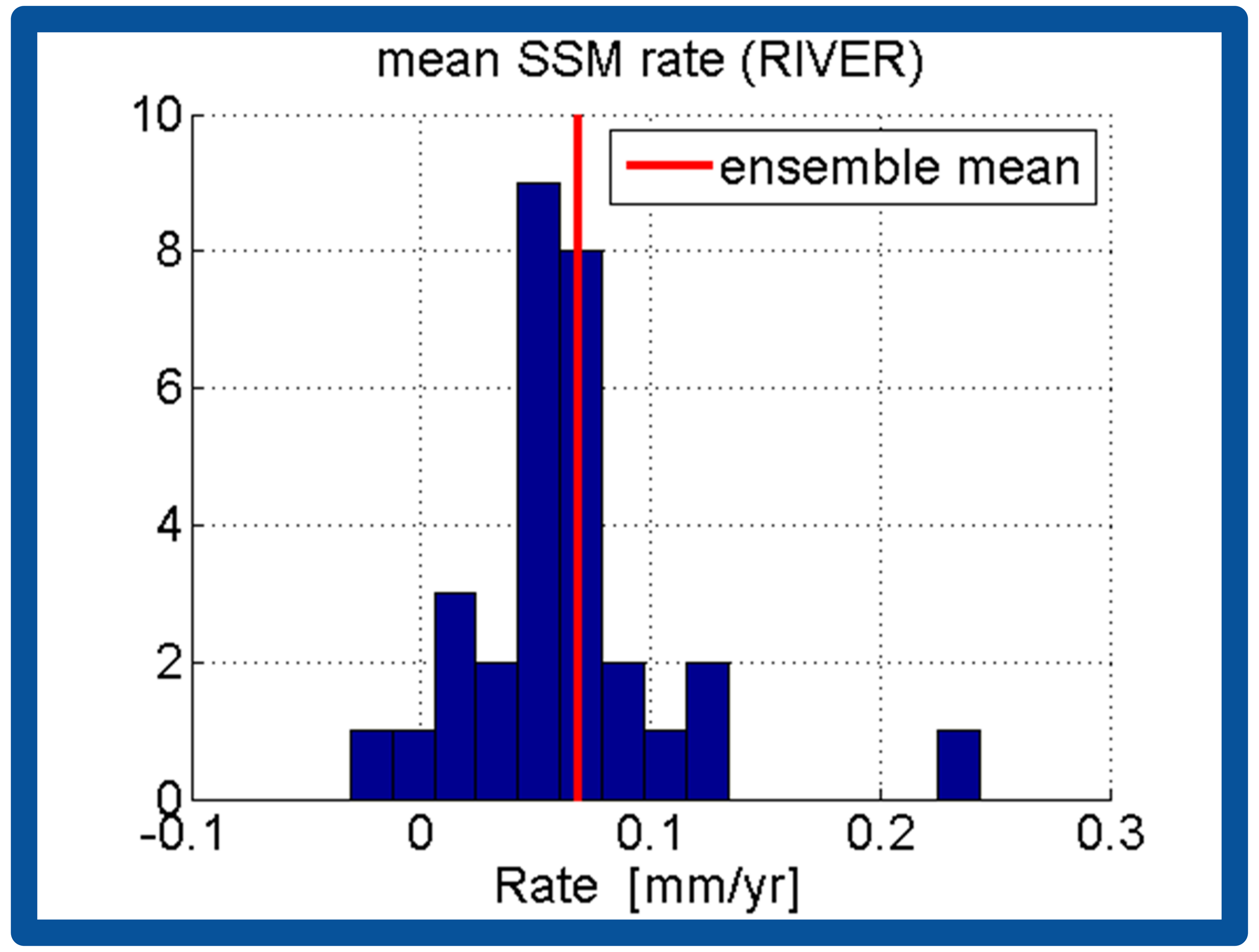


Time period		WGHM	GRACE	INV
Jan. 2003 – Aug. 2016	SSM mean rate [mm/yr]	0.71 ± 0.16	-0.23 ± 0.08	-0.44 ± 0.06
	Acceleration [mm/yr²]	-0.35 ± 0.15	-0.10 ± 0.06	-0.15 ± 0.08
Jan. 2003 – Dec. 2008	SSM mean rate [mm/yr]	2.75 ± 0.35	0.17 ± 0.18	-0.12 ± 0.17
	Acceleration [mm/yr²]	-0.73 ± 0.27	-0.00 ± 0.10	-0.14 ± 0.14
Dec. 2008 – Aug. 2016	SSM mean rate [mm/yr]	-0.59 ± 0.28	-0.57 ± 0.13	-0.65 ± 0.10
	Acceleration [mm/yr²]	-0.05 ± 0.22	-0.17 ± 0.08	-0.15 ± 0.11

[1]significant = greater than 95% confidence interval

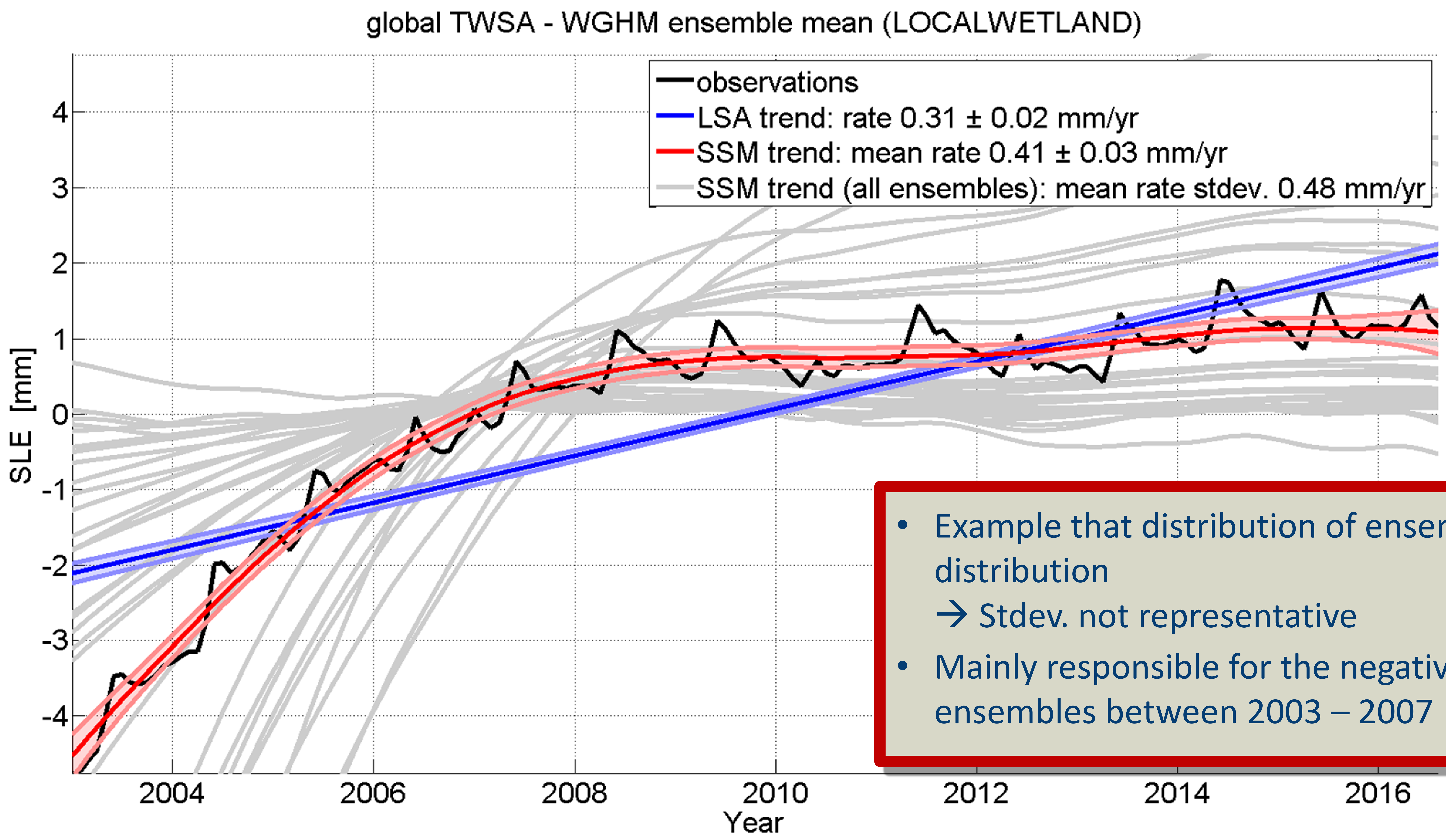
RESULTS – COMPARTMENTS

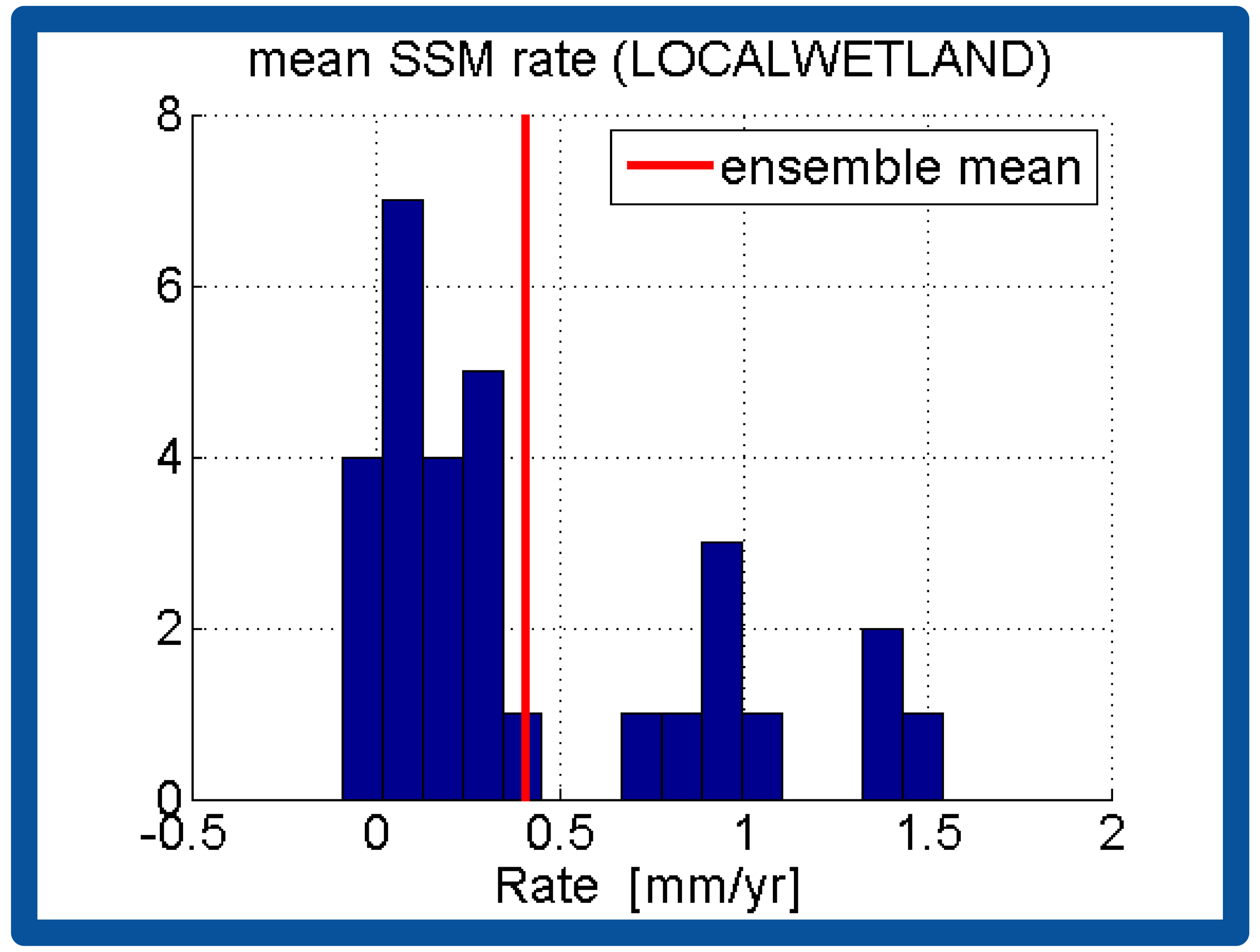




- Run of all ensembles relatively similar
- Gaussian like distribution
- Similar for canopy, global wetland, local lake, reservoir snow, soil

RESULTS – COMPARTMENTS

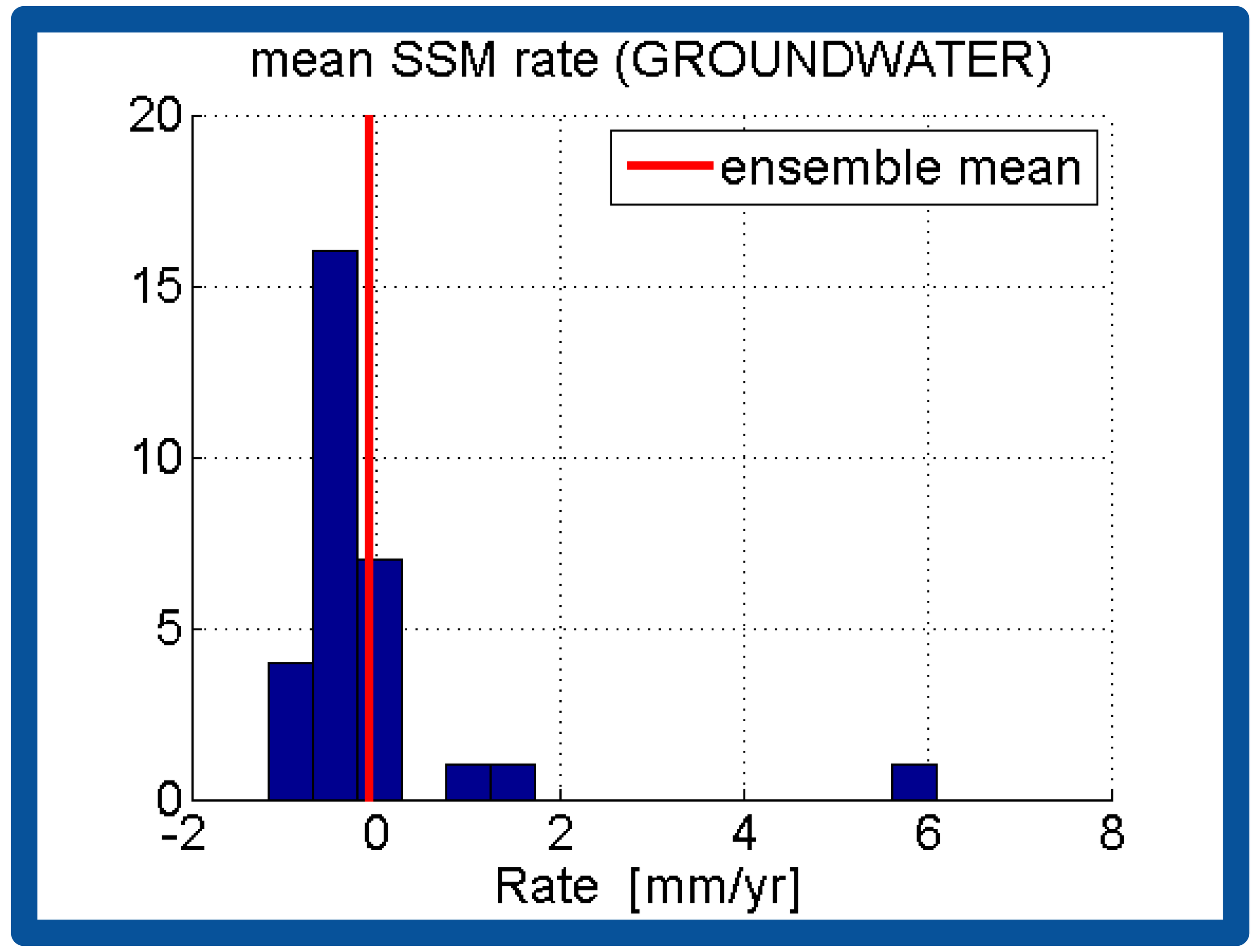


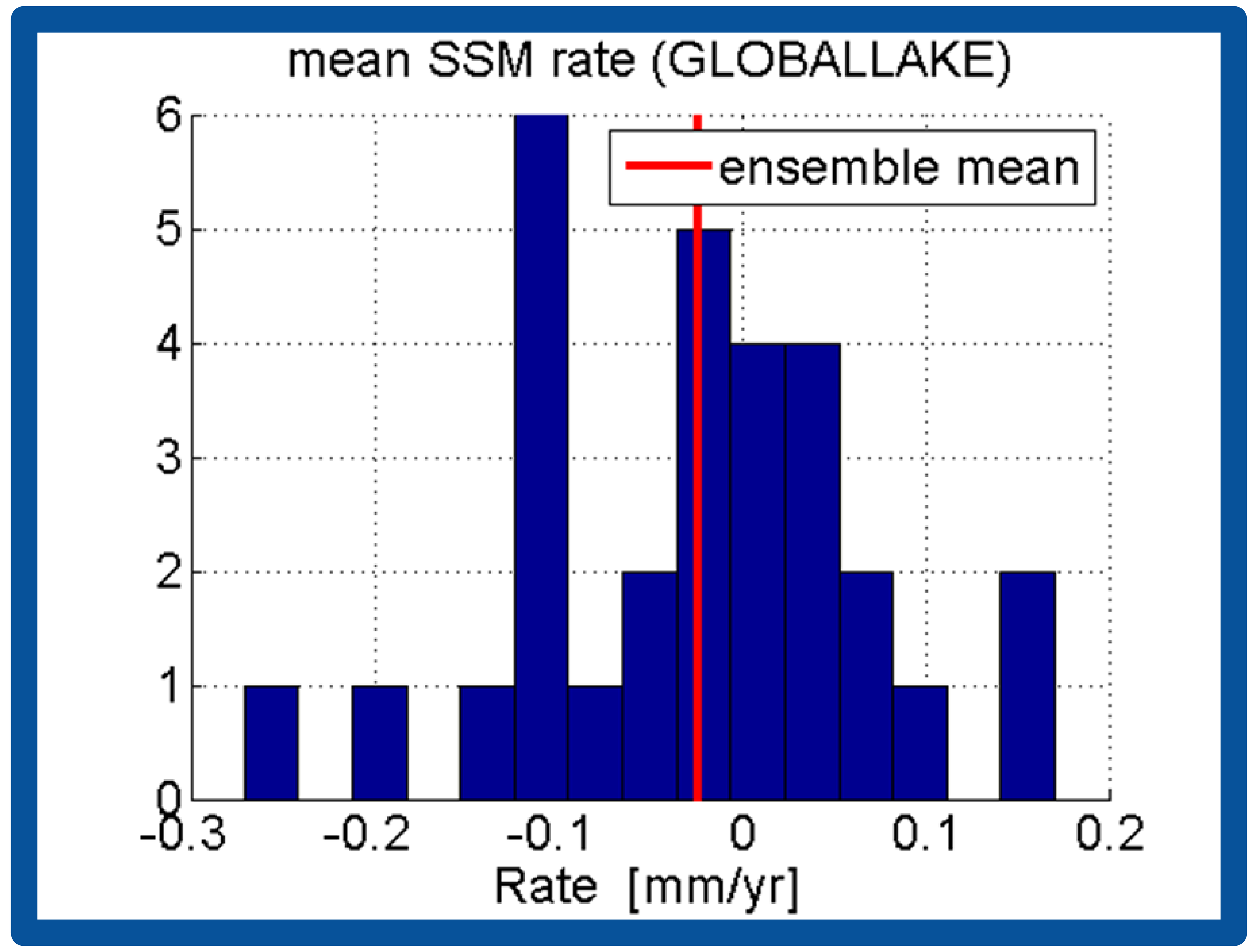


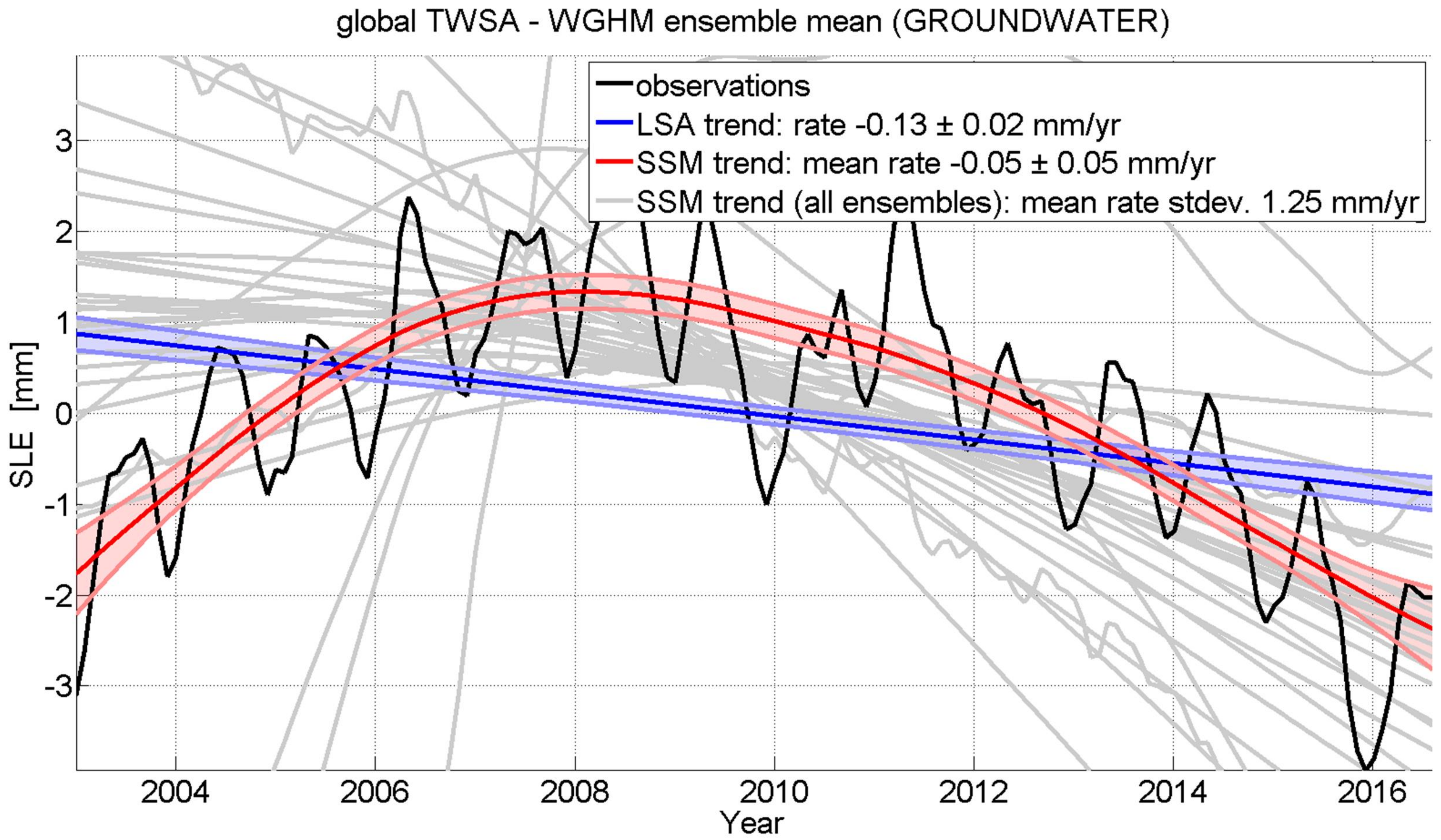
- Example that distribution of ensembles does not follow a normal distribution
  → Stdev. not representative
- Mainly responsible for the negative values of the WGHM-based ensembles between 2003 – 2007

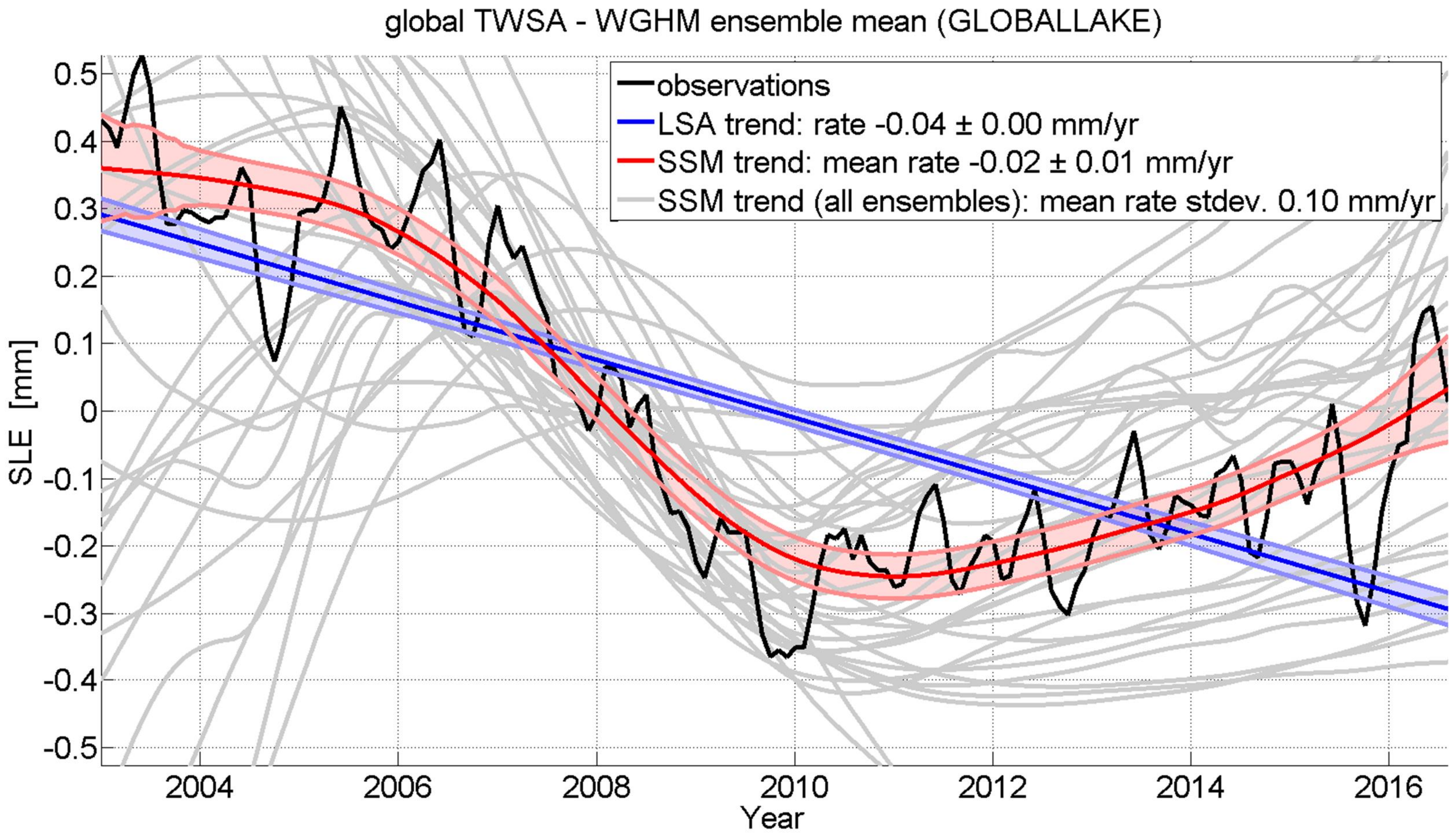
RESULTS – COMPARTMENTS

- Most arbitrary ensemble trends compared to other compartments
- Global lake: Another long periodic signal?
- Groundwater: Has a large contribution to uncertainty of WGHM due to the high amplitudes









CONCLUSION & OUTLOOK

Time period		WGHM	GRACE	INV
Jan. 2003 – Aug. 2016	SSM mean rate [mm/yr]	0.71 ± 0.16 (± 1.51*)	-0.23 ± 0.08 (± 0.03*)	-0.44 ± 0.06
	Acceleration [mm/yr^2]	-0.35 ± 0.15	-0.10 ± 0.06	-0.15 ± 0.08
Jan. 2003 – Dec. 2008	SSM mean rate [mm/yr]	2.75 ± 0.35	0.17 ± 0.18	-0.12 ± 0.17
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	Acceleration [mm/yr^2]	-0.05 ± 0.22	-0.17 ± 0.08	-0.15 ± 0.11

*= stdev. based on SSM ensemble spread

- Agreement within 1σ between 3 techniques in terms of rate for Dec. 2008 – Aug. 2016
- No constant acceleration over Jan. 2003 – Aug. 2016
- Significant acceleration over Jan. 2003 – Dec. 2008 from WGHM
- No significant acceleration over Dec. 2008 – Aug. 2016 from all datasets
- WGHM: Stdev. based on the spread of SSM ensembles > Stdev. of SSM > Stdev. of LSA
- WGHM: Groundwater → Largest stdev.; Local wetland → Main contributor to the negative trend between 2003 – 2007

- Extend the SSM toolbox for using the priori standard deviation of observations as additional input to SSM method
- Perform analysis based on larger number of ensembles to compute more representative standard deviations

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Contact: B.Sc. Christian Mielke

s7chmiel@uni-bonn.de