

Time-variable gravity field determination from GRACE Follow-On data using the Celestial Mechanics Approach extended by empirical noise modelling

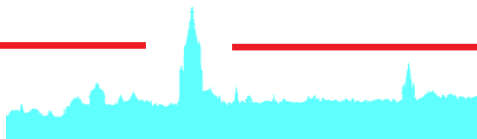
Martin Lasser, Ulrich Meyer, Daniel Arnold, Adrian Jäggi

Astronomical Institute, University of Bern, Switzerland

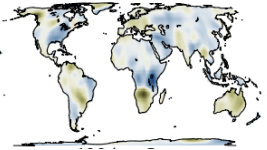
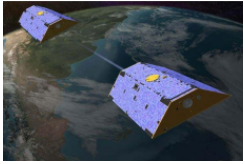
GRACE Follow-On Science Team Meeting 2022

18 October 2022

Potsdam, Germany



Operational processing



Basic parametrisation

- initial conditions 2x[6]
- accelerometer bias 2x[3]
- accelerometer scaling 2x[3]

parameters per arc 24

Additional parameters

- 15 min PCA per satellite in
 - radial 2x[96]
 - along-track 2x[96]
 - cross-track 2x[96]

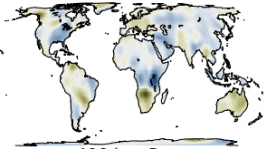
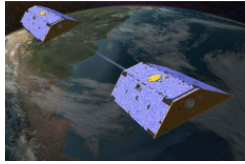
parameters per arc 576

in daily arcs (30 days):

- 18000 parameters,
- 17280 for the noise model
- + gravity field

→ frequently used in the
Celestial Mechanics Approach
[Beutler et al., 2010]

Operational processing



Basic parametrisation

- initial conditions 2x[6]
- accelerometer bias 2x[3]
- accelerometer scaling 2x[3]

parameters per arc 24

Additional parameters

- 15 min PCA per satellite in
 - radial 2x[96]
 - along-track 2x[96]
 - cross-track 2x[96]

parameters per arc 576

in daily arcs (30 days):

- 18000 parameters,
- 17280 for the noise model
- + gravity field

Force models

Gravity field	Internal AIUB static GRACE field
Astromomic bodies	JPL DE421 (all planets + Pluto)
Mean pole	Linear
Solid Earth tides	IERS2010
Solid Earth pole tides	IERS2010
Ocean tides	FES2014b (+ admittances from TUG)
Ocean pole tides	Desai
Atmospheric tides	AOD RL06
Atmospheric & oeanic dealiasing	AOD RL06
Relativistic effects	IERS2010

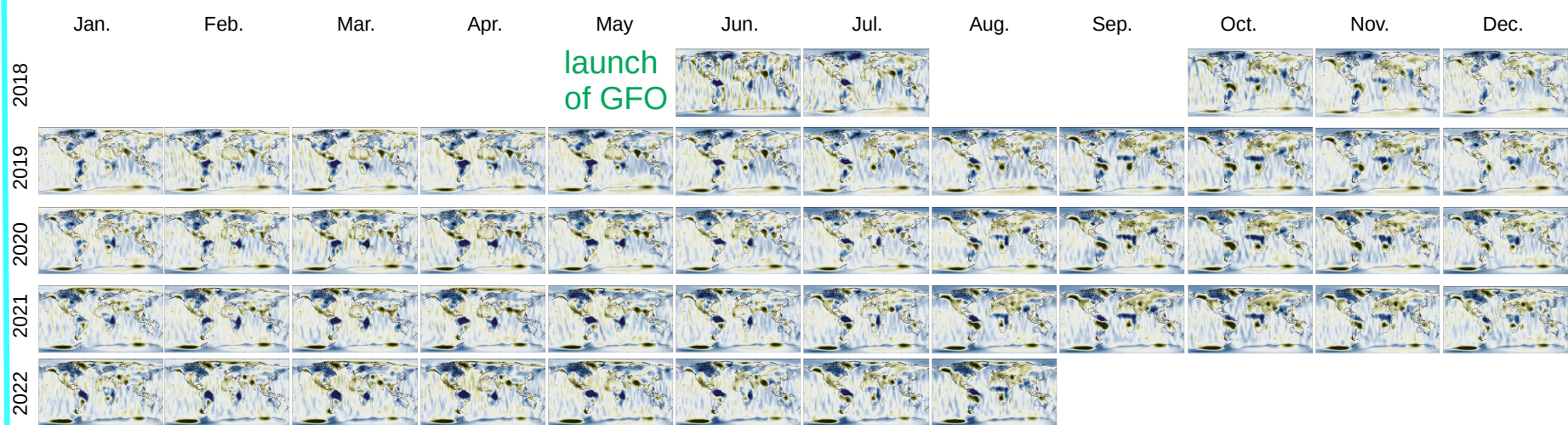
Non-conservative forces:
ACT from TUG

Processing – operational solution

$$\mathbf{N} = (\mathbf{A}^T \mathbf{P} \mathbf{A})$$

$$\mathbf{b} = \mathbf{A}^T \mathbf{P} \mathbf{l}$$

$$\hat{\mathbf{x}} = \mathbf{N}^{-1} \mathbf{b}$$



M. Lasser et al.: Time-variable gravity field determination from GRACE Follow-On data using the Celestial Mechanics Approach extended by empirical noise modelling, GRACE Follow-On Science Team Meeting, 18 October 2022

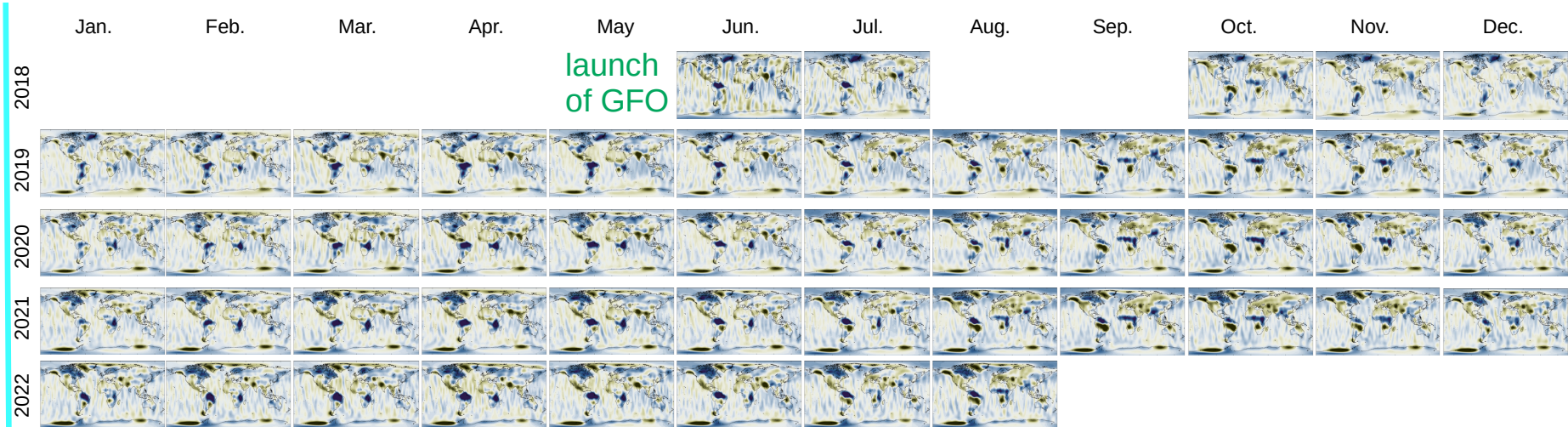


Processing – operational solution

$$\mathbf{N} = (\mathbf{A}^T \mathbf{P} \mathbf{A})$$

$$\mathbf{b} = \mathbf{A}^T \mathbf{P} \mathbf{l}$$

$$\hat{\mathbf{x}} = \mathbf{N}^{-1} \mathbf{b}$$



Facts

- operational since September 2020
- available at **ICGEM** as [AIUB-GRACE-FO_operational](#)
- continuation of AIUB-RL02
- current status: 49 months from June 2018 until August 2022

Features

- updated background models
- data screening with variance component estimation
- use of alternative GF2 Level 1B ACT product from TUG

Empirical Noise Modelling



Empirical noise modelling based on post-fit residuals

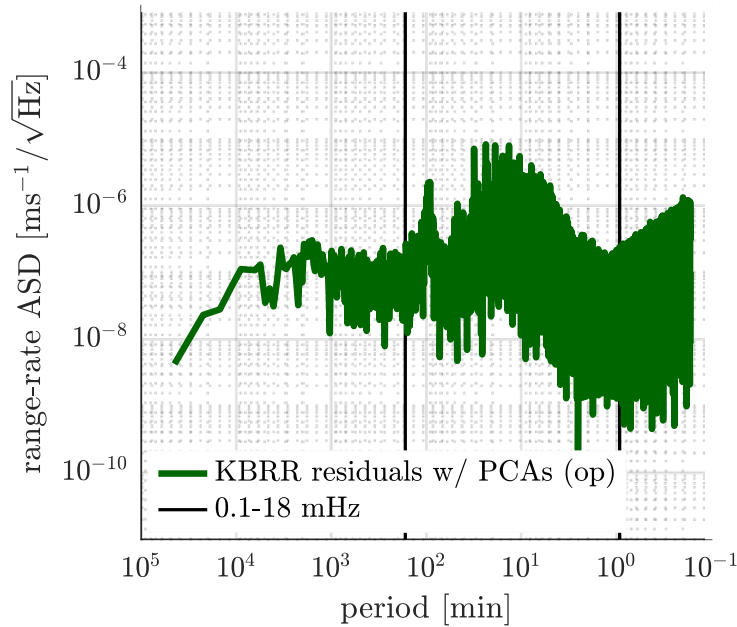
Least-squares

$$\mathbf{N} = (\mathbf{A}^T \mathbf{P} \mathbf{A})$$

$$\mathbf{b} = \mathbf{A}^T \mathbf{P} \mathbf{l}$$

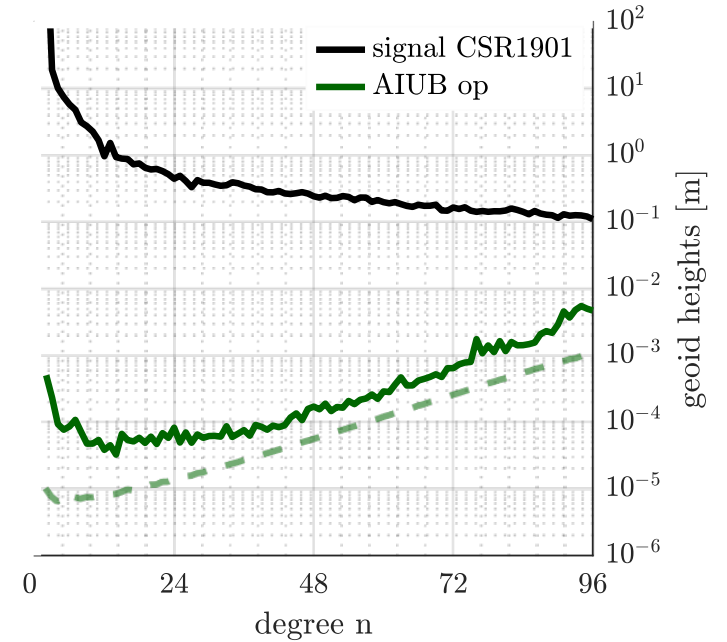
$$\hat{\mathbf{x}} = \mathbf{N}^{-1} \mathbf{b}$$

$$\hat{\mathbf{e}} = \mathbf{l} - \mathbf{A} \hat{\mathbf{x}}$$



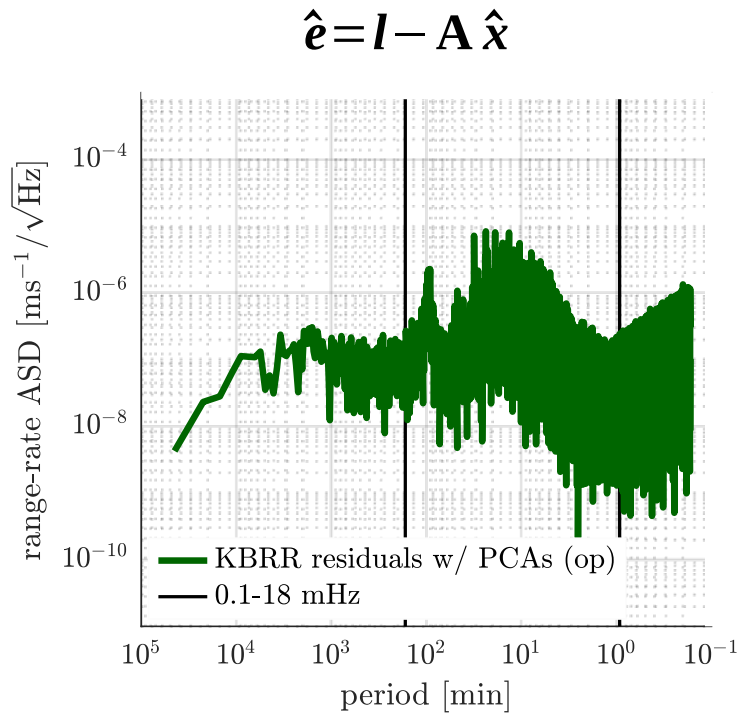
- information in the residuals (noise?)

$$\hat{\mathbf{x}} = \mathbf{N}^{-1} \mathbf{b}$$



- information in the parameters (signal?)

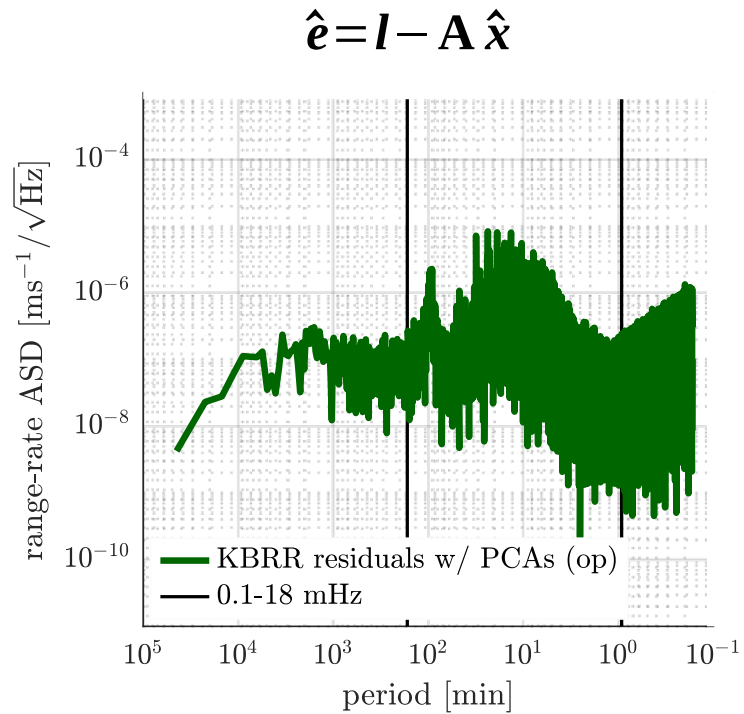
What do we expect from residuals?



The estimator is BLUE
(best – linear – unbiased) if

- $E(\hat{\mathbf{x}}) = \mathbf{x}$
- $E(\mathbf{e}|\mathbf{x}) = E(\hat{\mathbf{e}}) = \mathbf{0}$
- $D(\mathbf{e}|\mathbf{x}, \sigma_0^2) = D(\mathbf{l}|\sigma_0^2) = \sigma_0^2 \mathbf{P}^{-1}$
 $= \sigma_0^2 \mathbf{Q}_{ee} = \sigma_0^2 \mathbf{Q}_{ll}$

What do we expect from residuals?



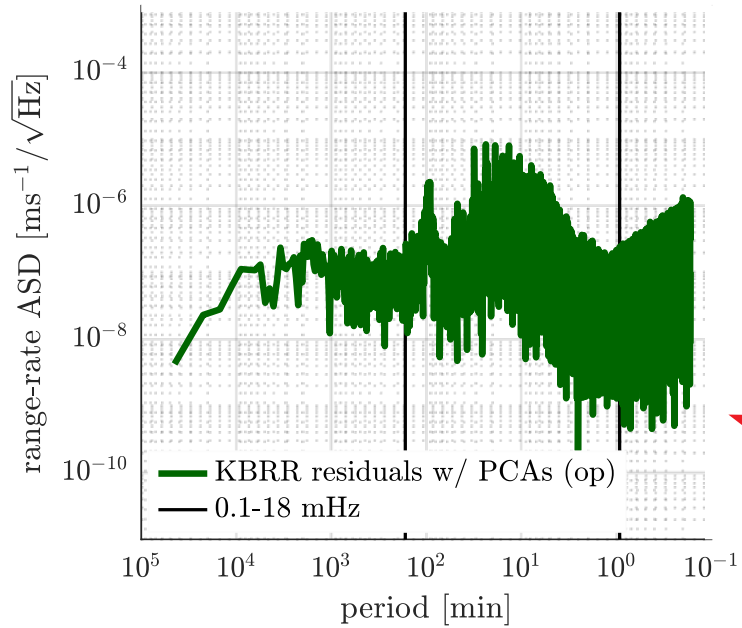
The estimator is BLUE
(best – linear – unbiased) if

- $E(\hat{\mathbf{x}}) = \mathbf{x}$
- $E(\mathbf{e}|\mathbf{x}) = E(\hat{\mathbf{e}}) = \mathbf{0}$
- $D(\mathbf{e}|\mathbf{x}, \sigma_0^2) = D(\mathbf{l}|\sigma_0^2) = \sigma_0^2 \mathbf{P}^{-1}$
 $= \sigma_0^2 \mathbf{Q}_{ee} = \sigma_0^2 \mathbf{Q}_{ll}$

$$\mathbf{P} = \frac{1}{\sigma_0^2} \mathbf{I}$$

What do we expect from residuals?

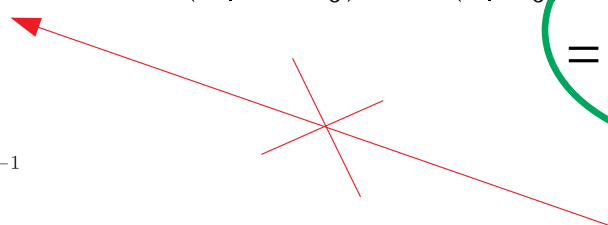
$$\hat{\mathbf{e}} = \mathbf{l} - \mathbf{A} \hat{\mathbf{x}}$$



The estimator is BLUE
(best – linear – unbiased) if

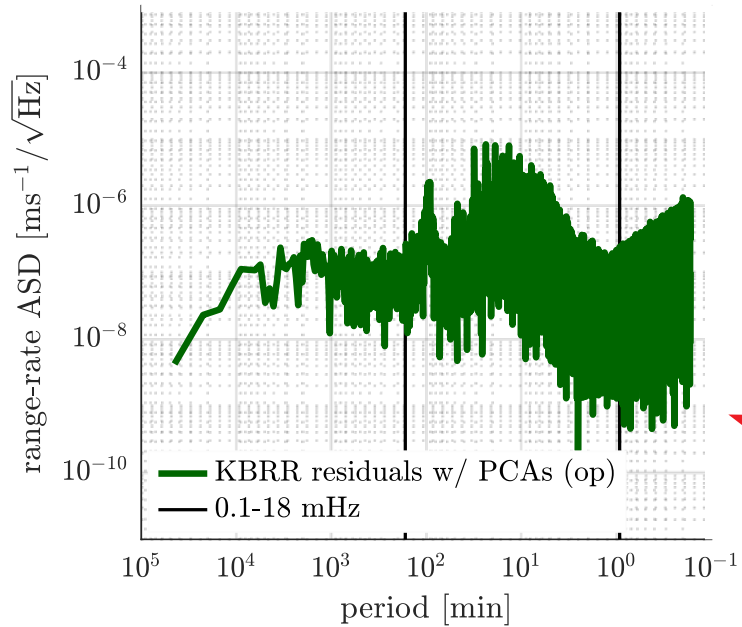
- $E(\hat{\mathbf{x}}) = \mathbf{x}$
- $E(\mathbf{e}|\mathbf{x}) = E(\hat{\mathbf{e}}) = \mathbf{0}$
- $D(\mathbf{e}|\mathbf{x}, \sigma_0^2) = D(\mathbf{l}|\sigma_0^2) = \sigma_0^2 \mathbf{P}^{-1}$
 $= \sigma_0^2 \mathbf{Q}_{ee} = \sigma_0^2 \mathbf{Q}_{ll}$

$$\mathbf{P} = \frac{1}{\sigma_0^2} \mathbf{I}$$



What do we expect from residuals?

$$\hat{\mathbf{e}} = \mathbf{l} - \mathbf{A} \hat{\mathbf{x}}$$



The estimator is BLUE
(best – linear – unbiased) if

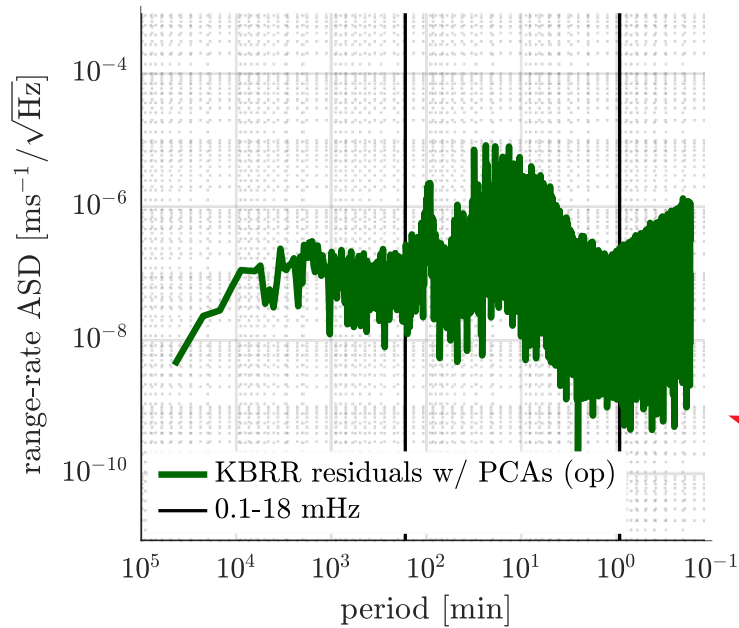
- $E(\hat{\mathbf{x}}) = \mathbf{x}$
- $E(\mathbf{e}|\mathbf{x}) = E(\hat{\mathbf{e}}) = \mathbf{0}$
- $D(\mathbf{e}|\mathbf{x}, \sigma_0^2) = D(\mathbf{l}|\sigma_0^2) = \sigma_0^2 \mathbf{P}^{-1}$
 $= \sigma_0^2 \mathbf{Q}_{ee} = \sigma_0^2 \mathbf{Q}_{ll}$

$$\mathbf{P} = \frac{1}{\sigma_0^2} \mathbf{I}$$

$\hat{\mathbf{x}} = \mathbf{N}^{-1} \mathbf{b}$	unbiased
$\mathbf{C}_{\hat{\mathbf{x}}\hat{\mathbf{x}}} = \sigma_0^2 (\mathbf{A}^T \mathbf{P} \mathbf{A})^{-1}$	biased

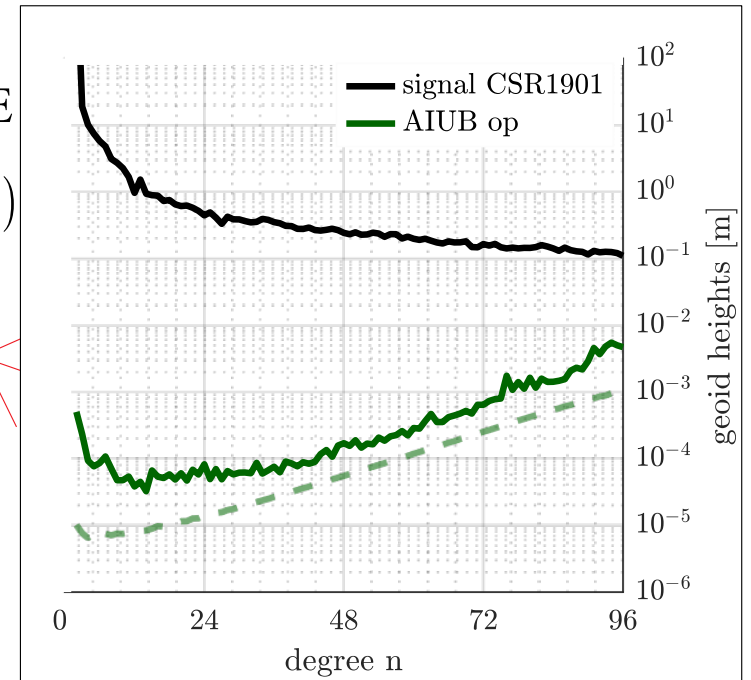
What do we expect from residuals?

$$\hat{\mathbf{e}} = \mathbf{l} - \mathbf{A} \hat{\mathbf{x}}$$



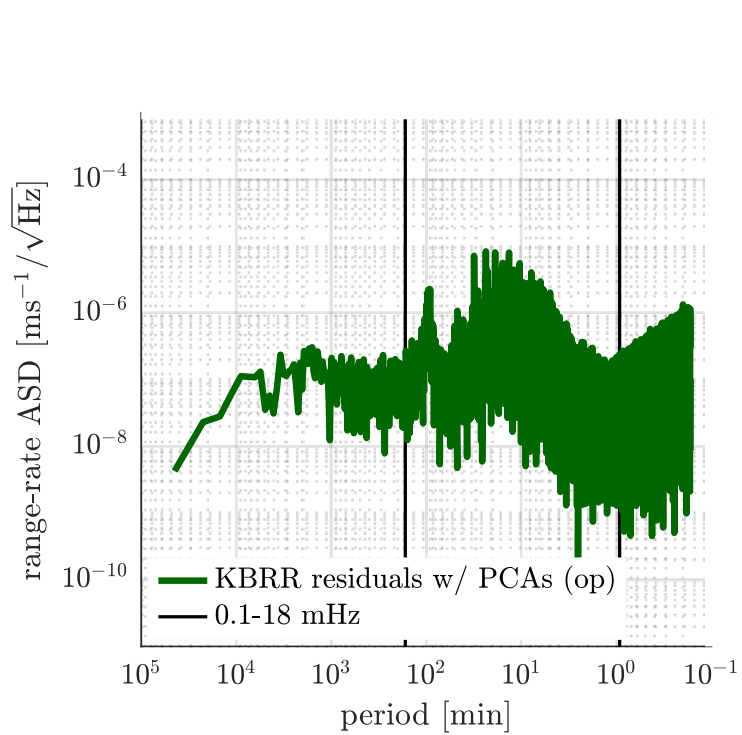
The estimator is BLUE
(best – linear – unbiased) if

- $E(\hat{\mathbf{x}}) = \mathbf{x}$
- $E(\mathbf{e}|\mathbf{x}) = \mathbf{0}$
- $D(\mathbf{e}|\mathbf{x}, \sigma_0^2)$



$\hat{\mathbf{x}} = \mathbf{N}^{-1} \mathbf{b}$	unbiased
$\mathbf{C}_{\hat{\mathbf{x}}\hat{\mathbf{x}}} = \sigma_0^2 (\mathbf{A}^T \mathbf{P} \mathbf{A})^{-1}$	biased

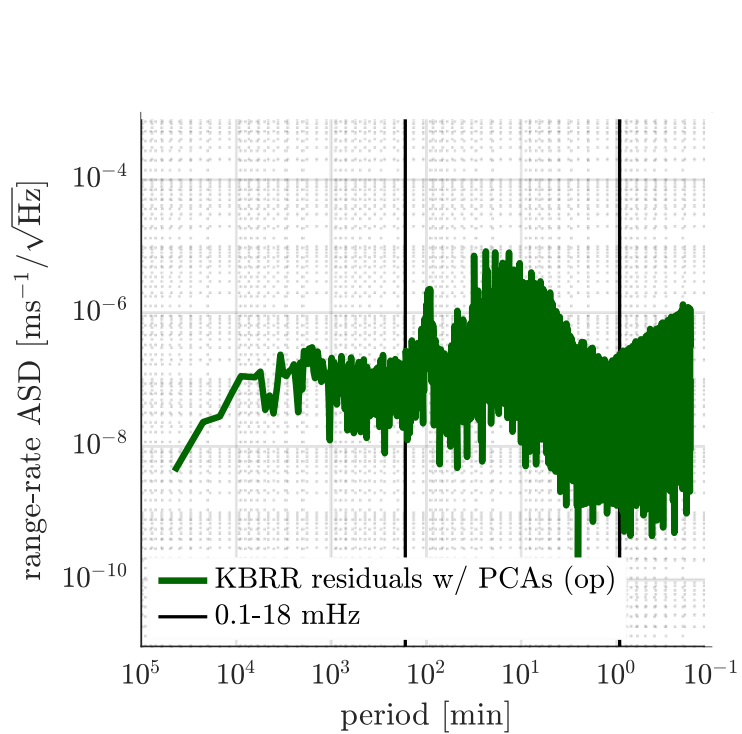
Auto-covariance function



$$\hat{\mathbf{e}} = \mathbf{l} - \mathbf{A} \hat{\mathbf{x}} \quad (\text{post-fit residuals})$$

$$\text{cov}(\Delta t_k) = \frac{1}{N} \sum_{i=0}^N \hat{\mathbf{e}}(t_i) \hat{\mathbf{e}}(t_i + \Delta t_k)$$

Auto-covariance function

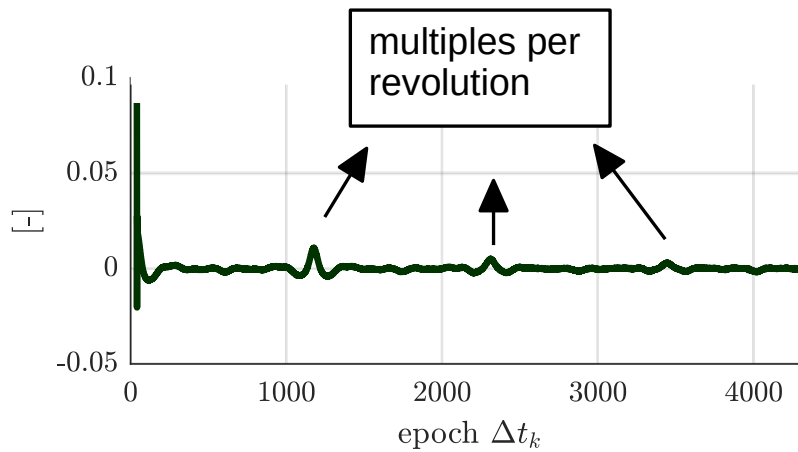


$$\hat{\mathbf{e}} = \mathbf{l} - \mathbf{A} \hat{\mathbf{x}} \quad (\text{post-fit residuals})$$

$$\text{cov}(\Delta t_k) = \frac{1}{N} \sum_{i=0}^N \hat{\mathbf{e}}(t_i) \hat{\mathbf{e}}(t_i + \Delta t_k)$$

- stationarity assumed
- biased estimation of auto-covariance
→ covariance matrix nondegenerate

Auto-covariance function

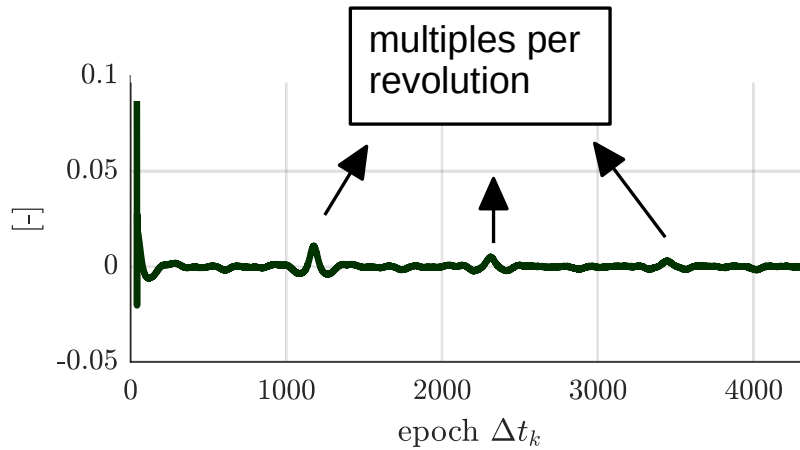


$$\hat{\mathbf{e}} = \mathbf{l} - \mathbf{A} \hat{\mathbf{x}} \quad (\text{post-fit residuals})$$

$$\text{cov}(\Delta t_k) = \frac{1}{N} \sum_{i=0}^N \hat{\mathbf{e}}(t_i) \hat{\mathbf{e}}(t_i + \Delta t_k)$$

- stationarity assumed
- biased estimation of auto-covariance
→ covariance matrix nondegenerate

Auto-covariance function and weight matrix

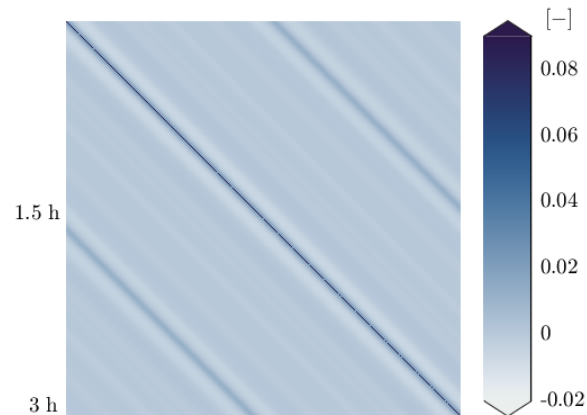


$$\hat{\mathbf{e}} = \mathbf{l} - \mathbf{A} \hat{\mathbf{x}} \quad (\text{post-fit residuals})$$

$$\text{cov}(\Delta t_k) = \frac{1}{N} \sum_{i=0}^N \hat{\mathbf{e}}(t_i) \hat{\mathbf{e}}(t_i + \Delta t_k)$$

- stationarity assumed
- biased estimation of auto-covariance
→ covariance matrix nondegenerate

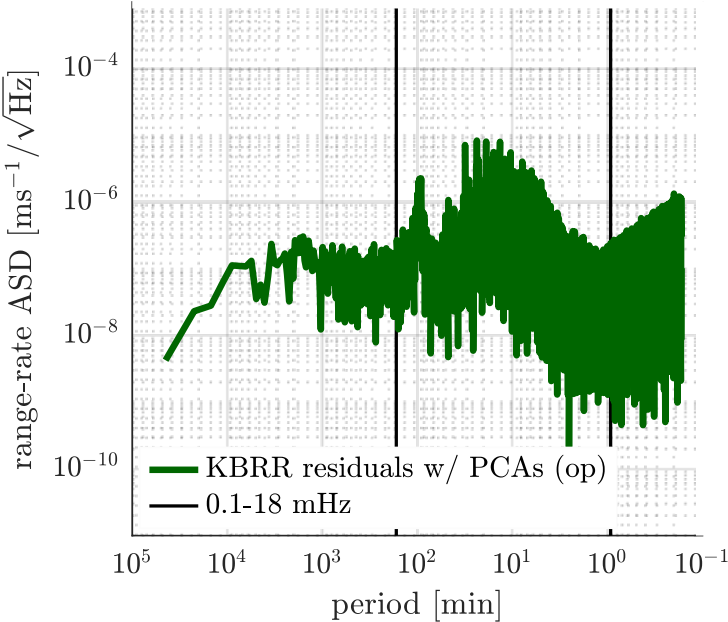
block
Toeplitz
matrix



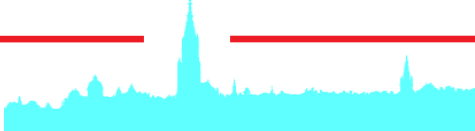
P

Auto-covariance function – examples

$$\hat{e} = I - A \hat{x}$$



M. Lasser et al.: Time-variable gravity field determination from GRACE Follow-On data using the Celestial Mechanics Approach extended by empirical noise modelling, GRACE Follow-On Science Team Meeting, 18 October 2022

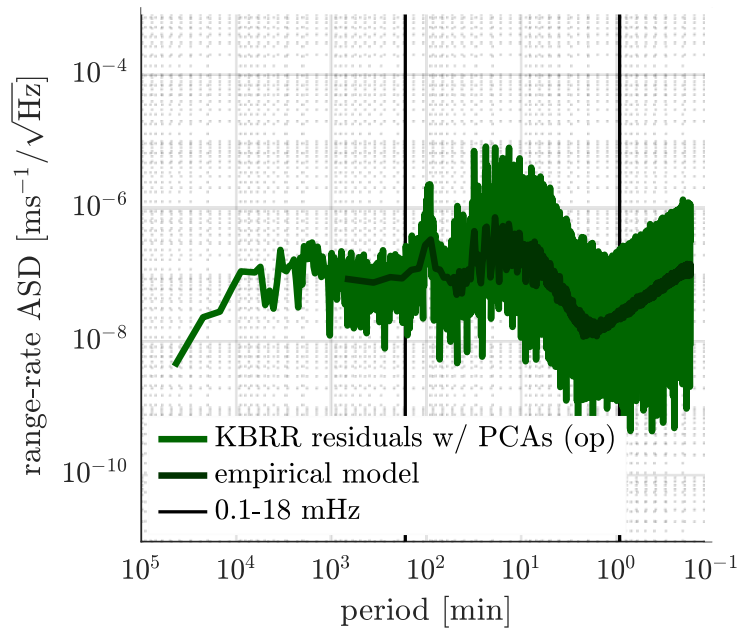


Auto-covariance function – examples

$$\hat{e} = l - A \hat{x}$$

$$\text{cov}(\Delta t_k) = \frac{1}{N} \cdot$$

$$\sum_{i=0}^N \hat{e}(t_i) \hat{e}(t_i + \Delta t_k)$$

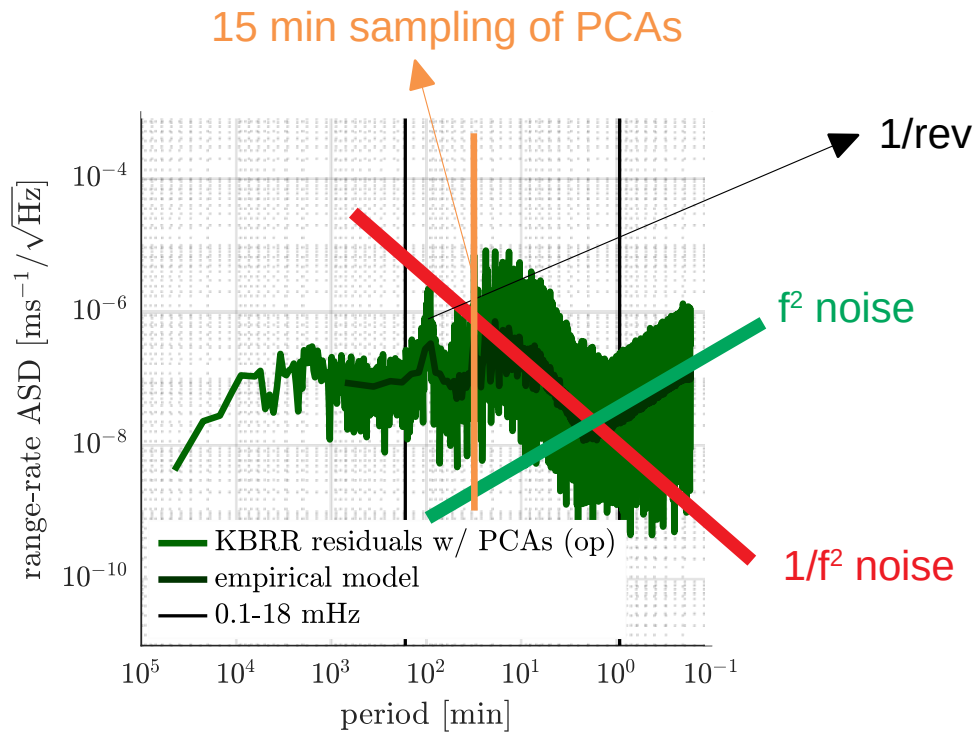


Auto-covariance function – examples

$$\hat{e} = l - A \hat{x}$$

$$\text{cov}(\Delta t_k) = \frac{1}{N} \cdot$$

$$\sum_{i=0}^N \hat{e}(t_i) \hat{e}(t_i + \Delta t_k)$$

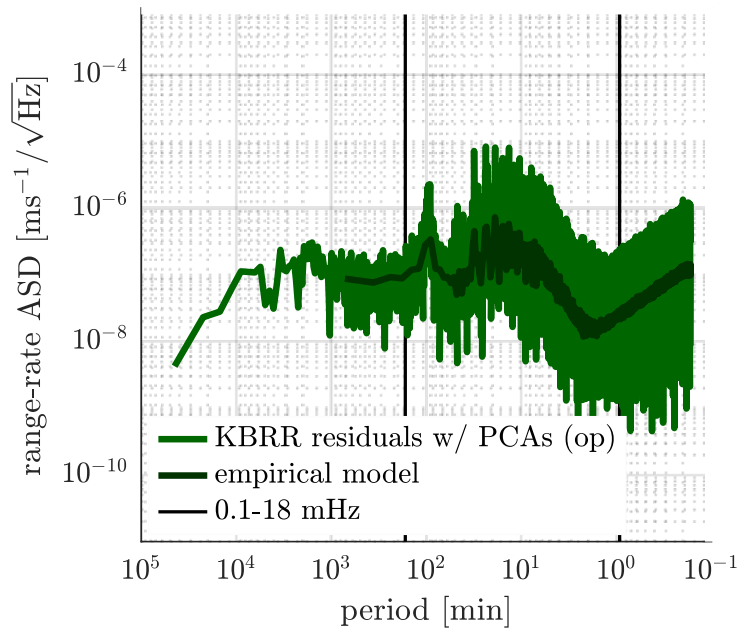


Auto-covariance function – examples

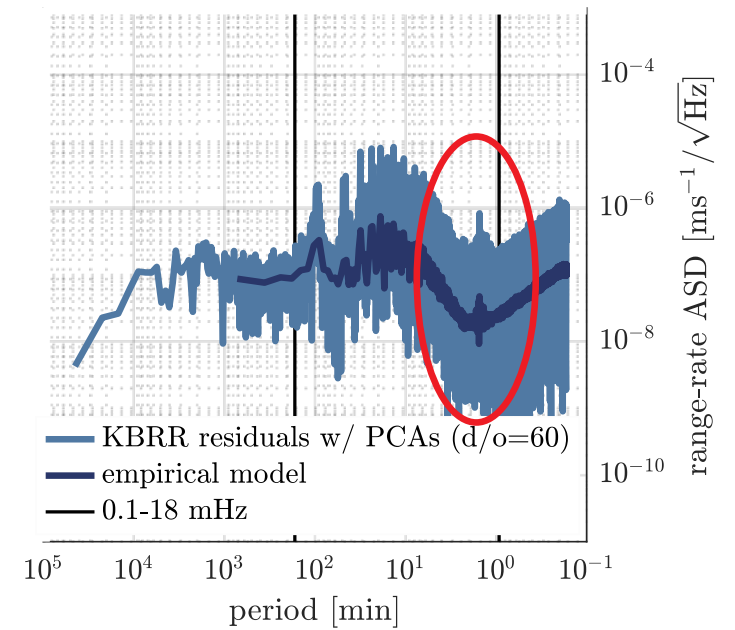
$$\hat{e} = I - A \hat{x}$$

$$\text{cov}(\Delta t_k) = \frac{1}{N} \cdot$$

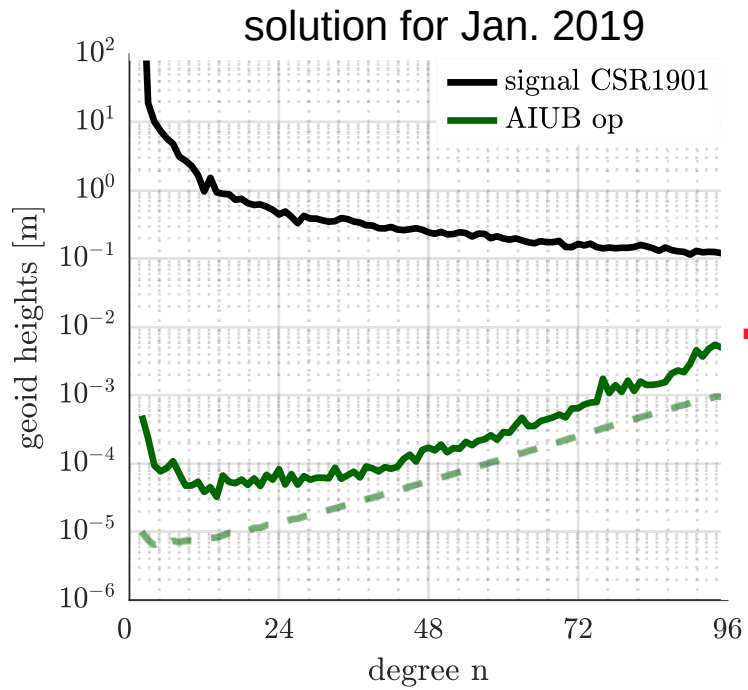
$$\sum_{i=0}^N \hat{e}(t_i) \hat{e}(t_i + \Delta t_k)$$



truncation at d/o=60
(artefact → bias)
is reflected

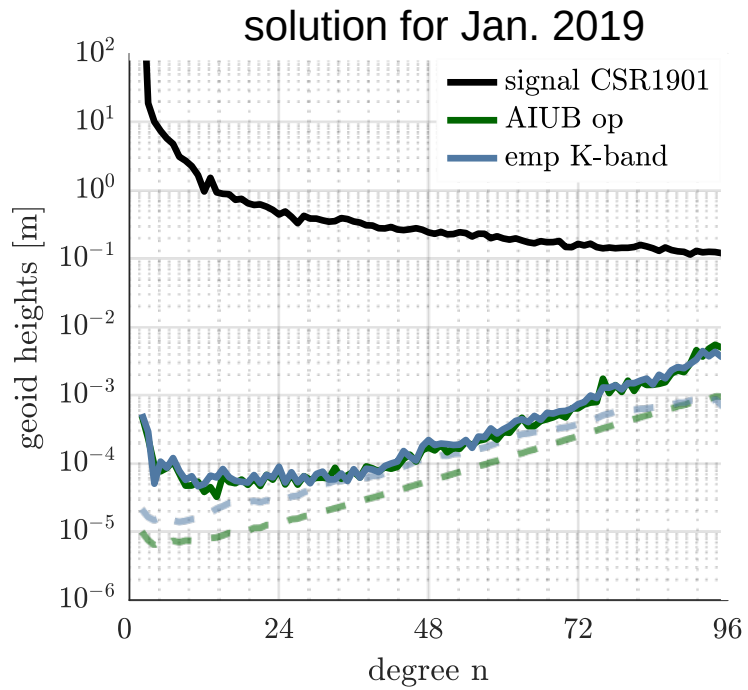


Results of empirical modelling – gravity field



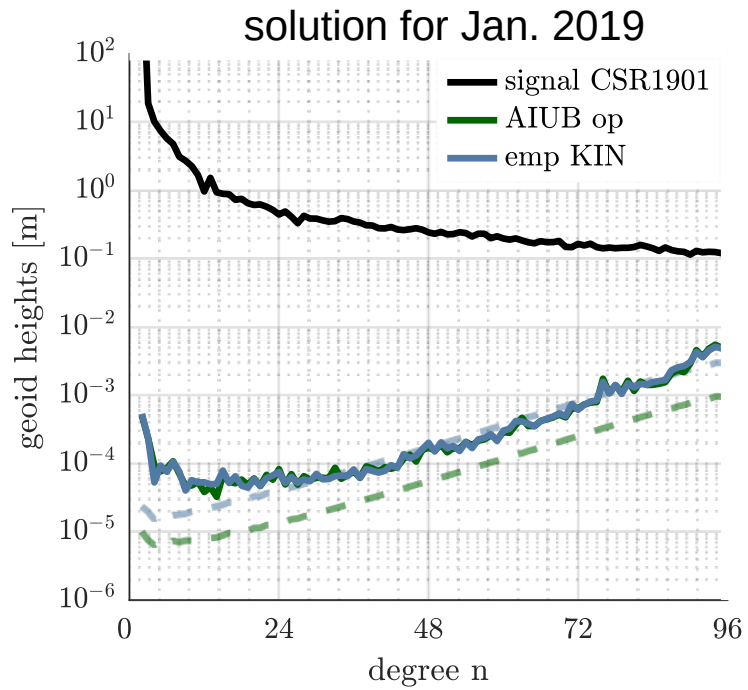
■ formal errors too optimistic compared to the assessed noise

Results of empirical modelling (K-band) – gravity field



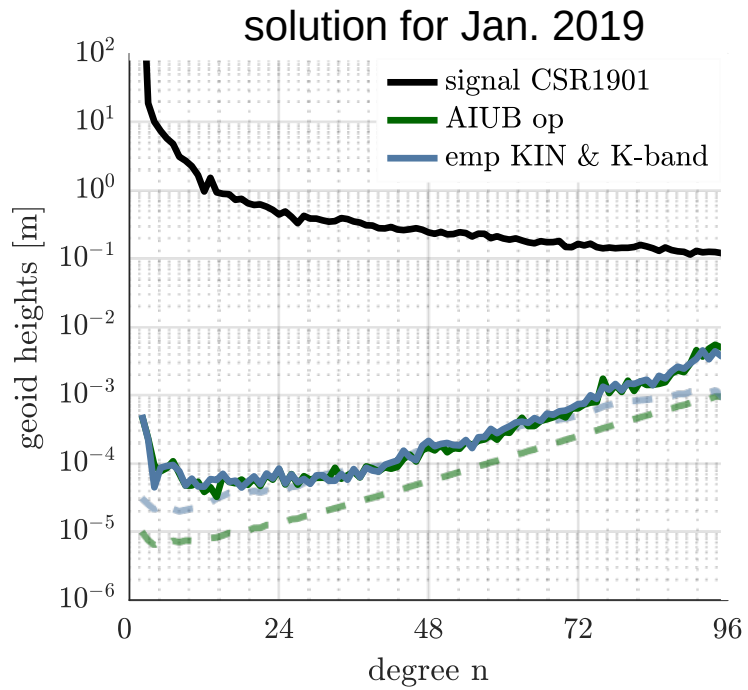
- formal errors reflect assessed noise very well
- including features of resonance orders

Results of empirical modelling (KIN) – gravity field



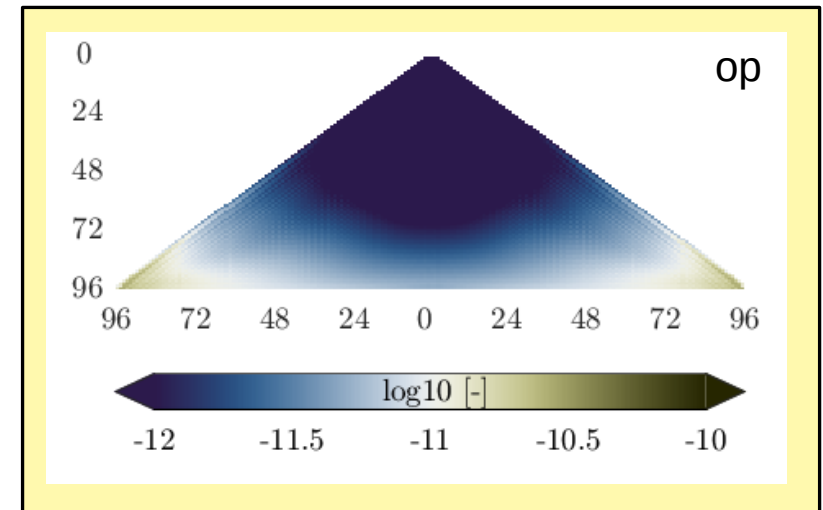
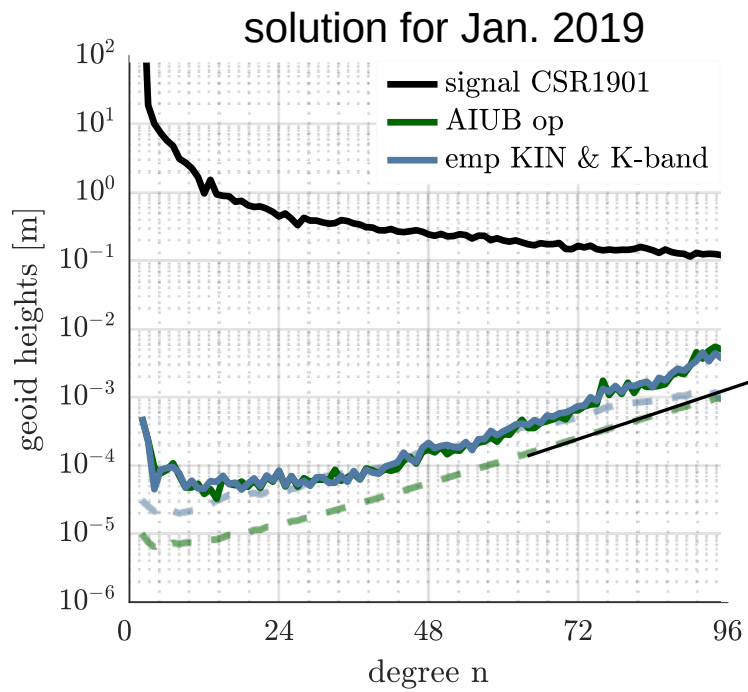
- formal errors reflect assessed noise very well
- basically the formal error curve is shifted

Results of empirical modelling (KIN & K-band) – gravity field

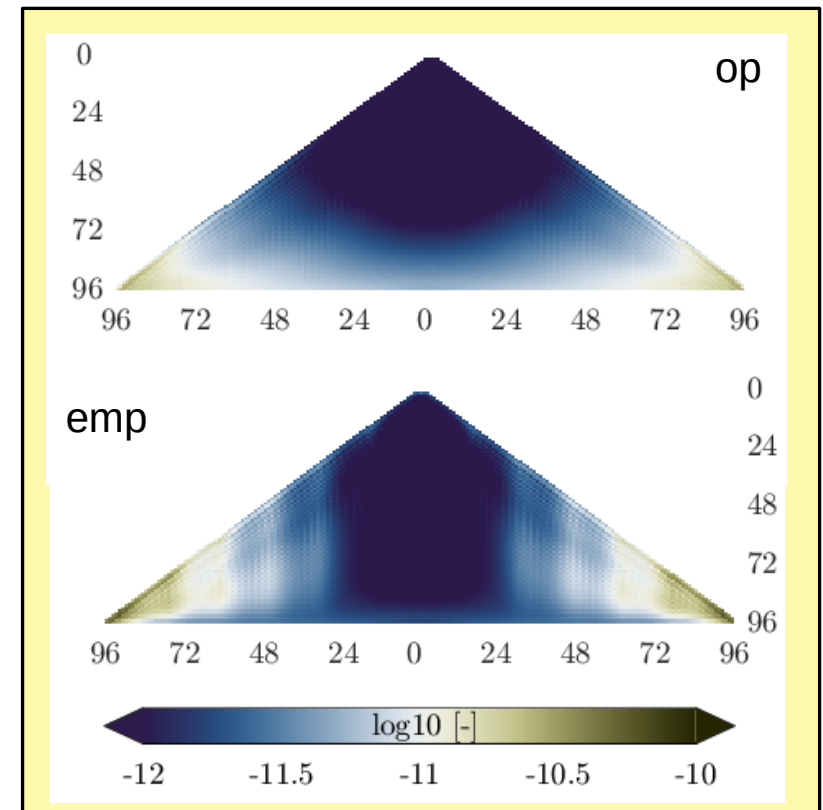
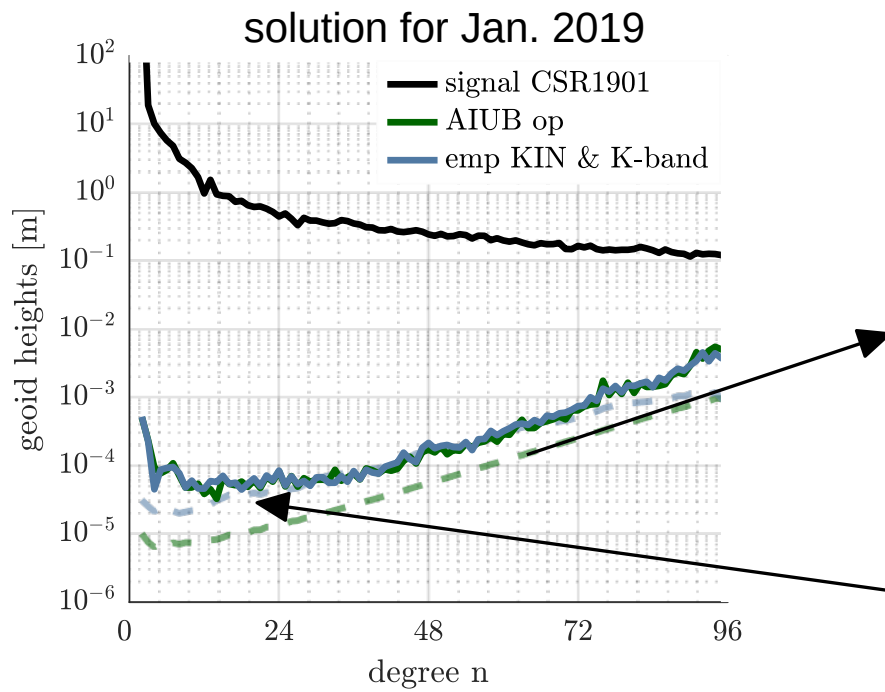


- formal errors reflect assessed noise very well
- including features of resonance orders

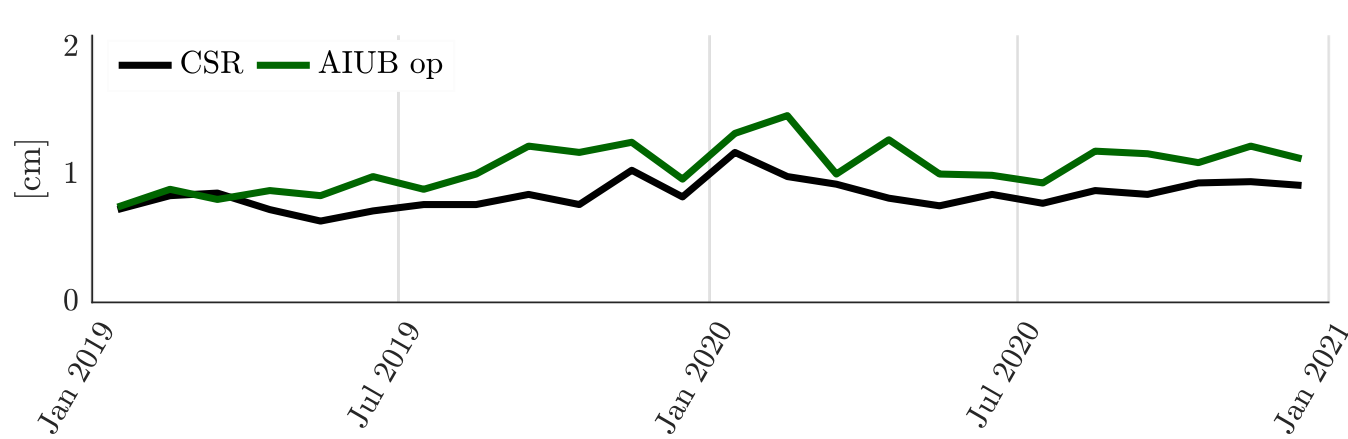
Results of empirical modelling – formal errors



Results of empirical modelling – formal errors



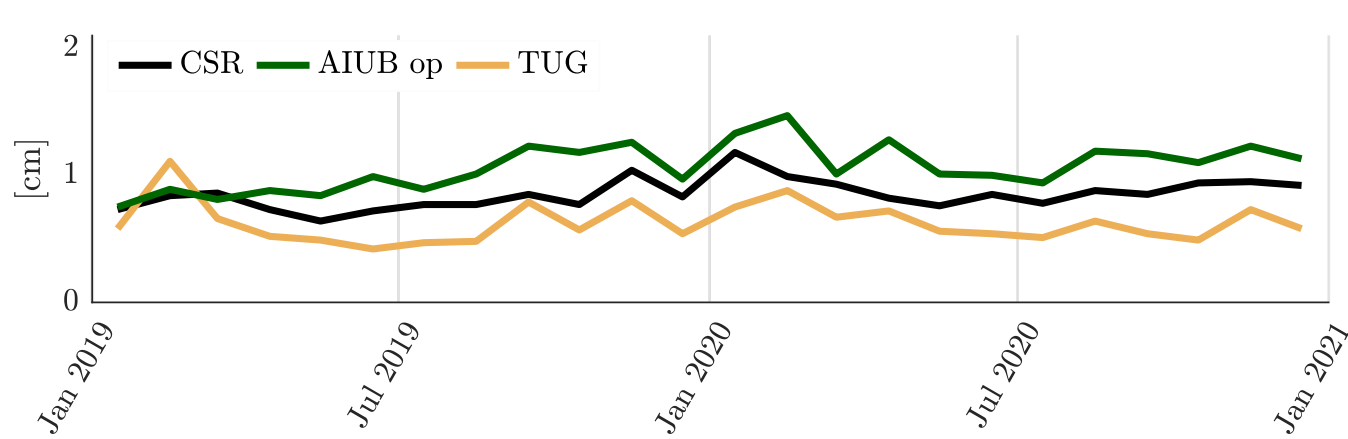
Results of empirical modelling – RMS over the ocean



M. Lasser et al.: Time-variable gravity field determination from GRACE Follow-On data using the Celestial Mechanics Approach extended by empirical noise modelling, GRACE Follow-On Science Team Meeting, 18 October 2022



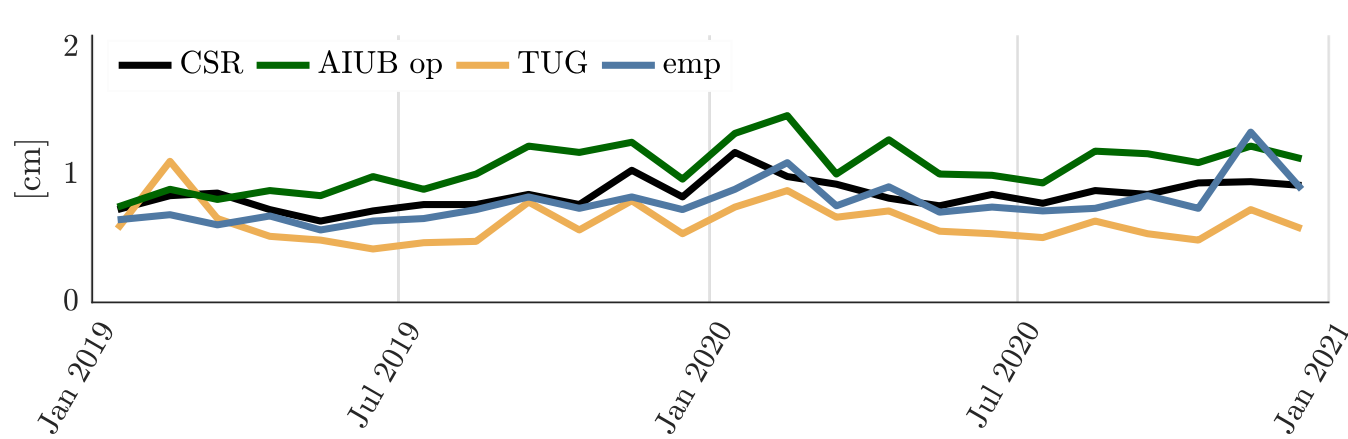
Results of empirical modelling – RMS over the ocean



M. Lasser et al.: Time-variable gravity field determination from GRACE Follow-On data using the Celestial Mechanics Approach extended by empirical noise modelling, GRACE Follow-On Science Team Meeting, 18 October 2022



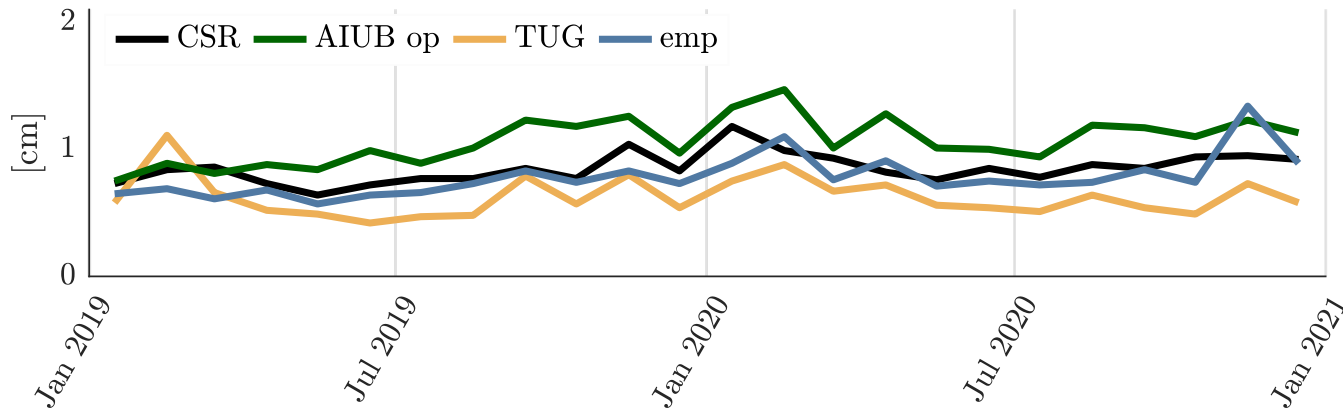
Results of empirical modelling – RMS over the ocean



M. Lasser et al.: Time-variable gravity field determination from GRACE Follow-On data using the Celestial Mechanics Approach extended by empirical noise modelling, GRACE Follow-On Science Team Meeting, 18 October 2022



Results of empirical modelling – summary

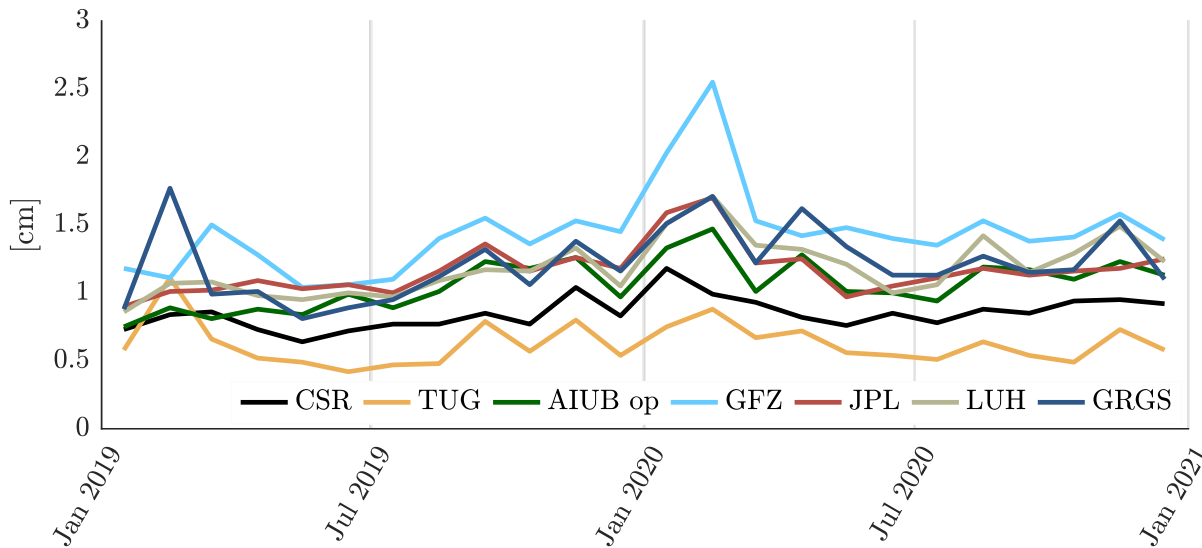


- possible on any (stationary) residuals time series
 - additional parameters can be reduced as stationary behaviour can be absorbed
 - formal errors much more realistic and show resonance orders (if correlation length > 3 h)
 - no constraints needed
 - no/few a priori knowledge needed
-
- iterations required (might be time consuming)
 - memory consumption and inversion time dependent on length of auto-covariance function

Performance in COST-G – RMS over the ocean



Combining time-variable gravity field solutions to provide for a product of improved quality, robustness and reliability

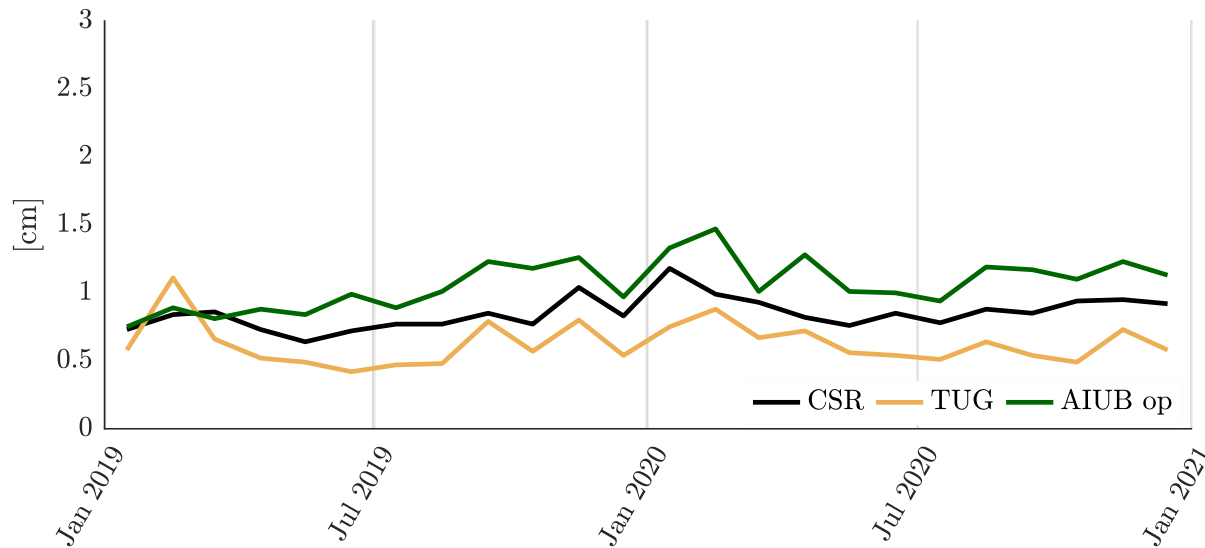


M. Lasser et al.: Time-variable gravity field determination from GRACE Follow-On data using the Celestial Mechanics Approach extended by empirical noise modelling, GRACE Follow-On Science Team Meeting, 18 October 2022

Performance in COST-G – RMS over the ocean



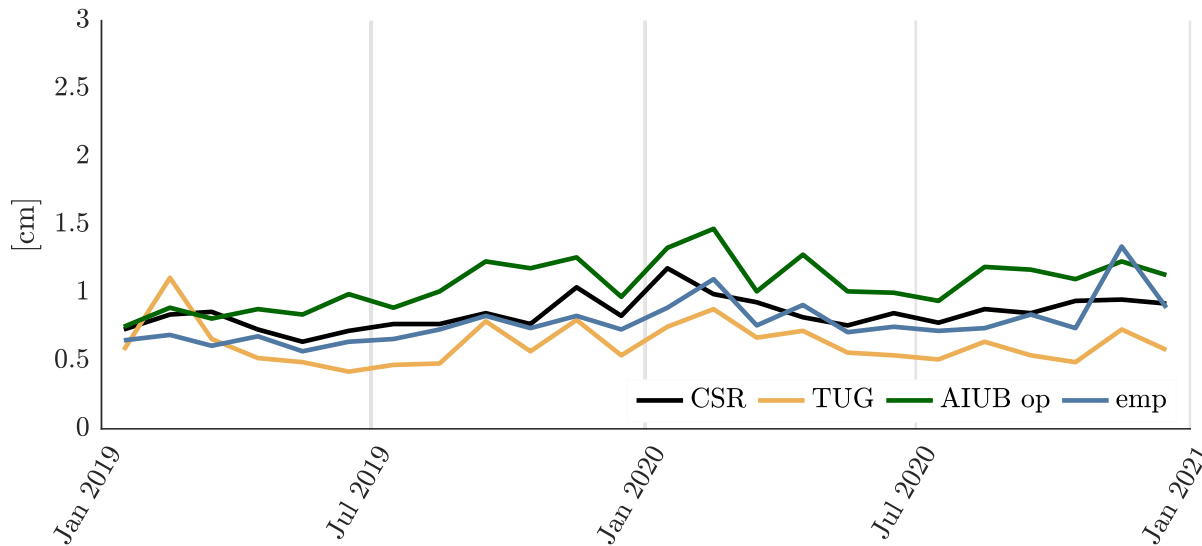
Combining time-variable gravity field solutions to provide for a product of improved quality, robustness and reliability



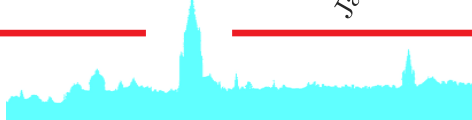
Performance in COST-G – RMS over the ocean



Combining time-variable gravity field solutions to provide for a product of improved quality, robustness and reliability



M. Lasser et al.: Time-variable gravity field determination from GRACE Follow-On data using the Celestial Mechanics Approach extended by empirical noise modelling, GRACE Follow-On Science Team Meeting, 18 October 2022

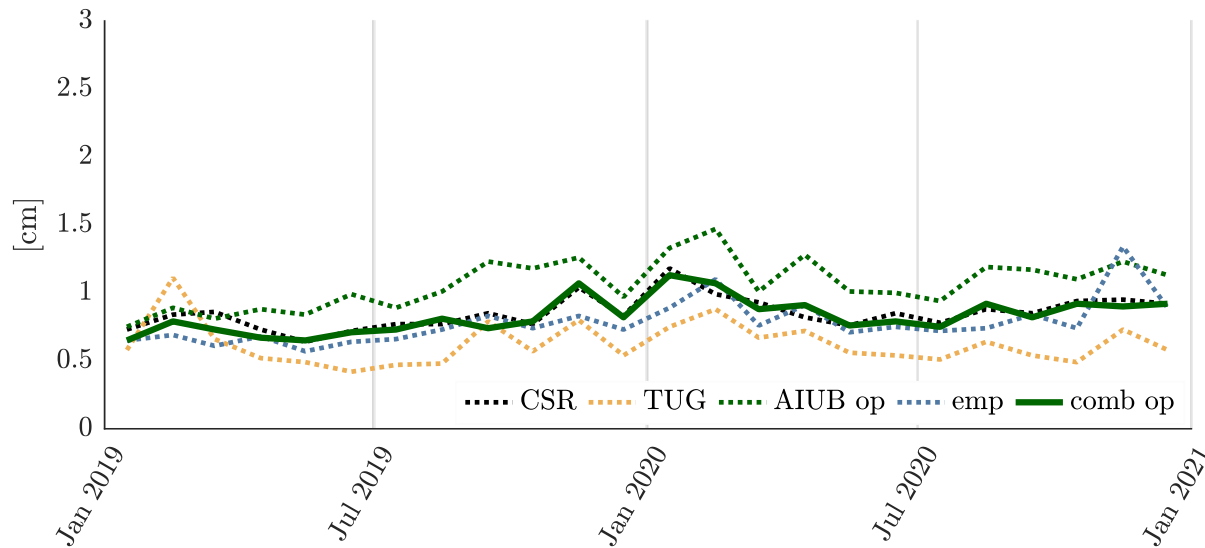


Performance in COST-G – RMS over the ocean



Combining time-variable gravity field solutions to provide for a product of improved quality, robustness and reliability

- Combination not at the level of the best individual solutions

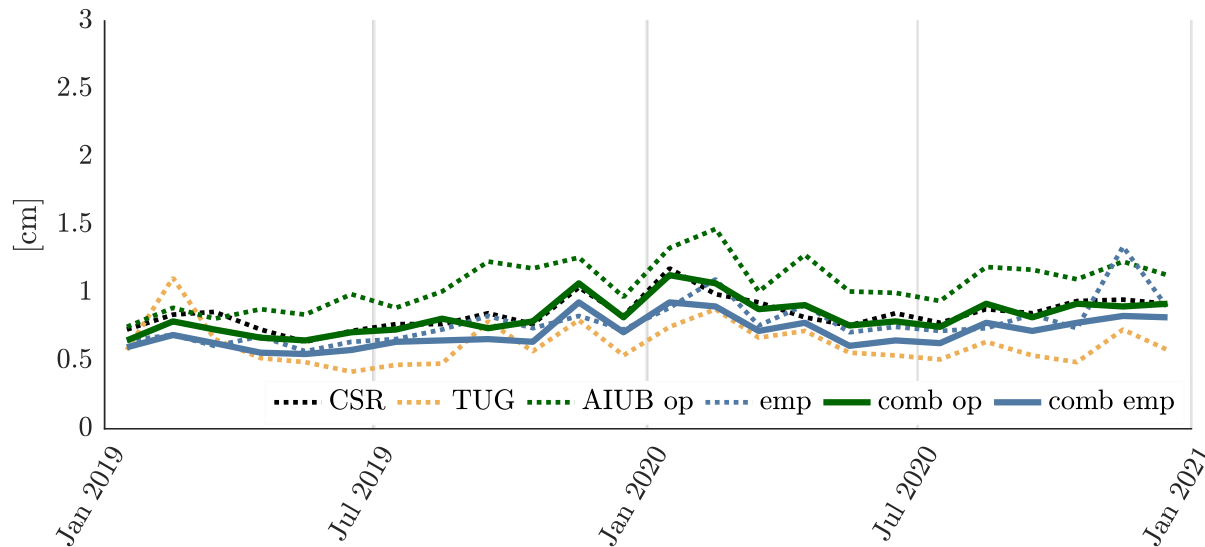


Performance in COST-G

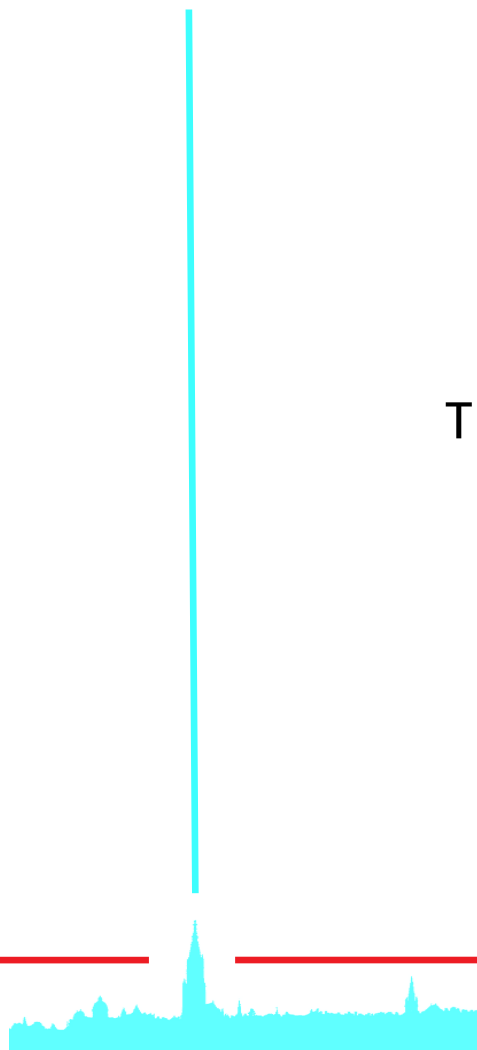


Combining time-variable gravity field solutions to provide for a product of improved quality, robustness and reliability

- (Combination not at the level of the best individual solutions)
- Combination significantly improved by the new processing scheme of one analysis centre



Thank you for your attention



References

Beutler, G., Jäggi, A., Mervart, L. and Meyer, U. [2010]: The celestial mechanics approach: theoretical foundations. Journal of Geodesy, vol. 84(10), pp. 605-624. <https://doi.org/10.1007/s00190-010-0401-7>

Ellmer, M. [2018]: Contributions to GRACE Gravity Field Recovery: Improvements in Dynamic Orbit Integration Stochastic Modelling of the Antenna Offset Correction, and Co-Estimation of Satellite Orientations. PhD thesis, Graz University of Technology, In Monographic Series TU Graz, number 1, Verlag der Technischen Universität Graz, Graz, Austria. <https://doi.org/10.3217/978-3-85125-646-8>

Jäggi, A., Meyer, U., Lasser, M., Jenny, B., Lopez, T., Flechtner, F., Dahle, C., Förste, C., Mayer-Gürr, T., Kvas, A., Lemoine, J.-M., Bourgogne, S., Weigelt, M. and Groh, A. [2020]: International Combination Service for Time-Varying Gravity Fields (COST-G) – Start of Operational Phase and Future Perspectives. In J. Freymueller, editor, International Association of Geodesy Symposia, pages 1–9, Springer Berlin-Heidelberg, Germany. https://doi.org/10.1007/1345_2020_109

Lasser, M., Meyer, U., Arnold, D. and Jäggi, A. [2020]: AIUB-GRACE-FO-operational - Operational GRACE Follow-On monthly gravity field solutions. <https://doi.org/10.5880/ICGEM.2020.001>

Kvas, A., Behzadpour, S., Ellmer, M., Klinger, B., Strasser, S., Zehentner, N. and Mayer-Gürr, T. [2019]: Overview and evaluation of a new GRACE-only gravity field time series. Journal of Geophysical Research: Solid Earth. ISSN 2169-9313. <https://doi.org/10.1029/2019JB017415>

NASA Jet Propulsion Laboratory (JPL) [2019]: GRACE-FO Monthly Geopotential Spherical Harmonics CSR Release 6.0. <https://doi.org/10.5067/GFL20-MC060>

