

Vertical deformation and residual altimeter systematic errors around continental Australia inferred from a Kalman-based approachMohammad-Hadi Rezvani¹, Christopher S. Watson¹, Matt A. King¹¹ School of Geography, Planning, and Spatial Sciences, University of Tasmania, Hobart, TAS, Australia**Contents of this file**

S1. Supplementary method	2
S1.1. Datasets.....	2
S1.2. Multi-stage solution approach.....	3
S1.2.1. Solution 1.....	3
S1.2.2. Solution 2.....	3
S1.2.3. Solution 3.....	4
S1.3. Preliminary analyses	6
S1.3.1. GPS-Krig VLM at TG locations.....	6
S1.3.2. Spectral noise analysis.....	7
S1.3.3. Semi-variogram analysis.....	9
S1.3.4. TG datum errors detection	10
S2. Supplementary results.....	11
S2.1. VLM estimates.....	11
S2.1.1. Linear VLM.....	11
S2.1.2. Nonlinear VLM	13
S2.2. Altimeter relative bias estimates	21
S2.3. Implications for coastal and offshore ASL	23
S2.4. Sensitivity analysis	29
S2.4.1. Impact of expanded altimeter dataset.....	29
S2.4.2. Impact of time-variable altimeter systematic errors.....	32
S2.4.3. Impact of nonlinear VLM estimates	34
S2.4.4. Impact of climate-induced variability	36
S2.4.5. Impact of zero-drift assumption.....	40
S2.5. Implications for the approach: differential oceanography	42
S2.6. Residuals and a posteriori analysis	43
References from the Supporting Information.....	53

Introduction

Here we present supporting materials including Figures and Tables that are referred to throughout the main manuscript, categorizing in “Supplementary Method” and “Supplementary Results” sections. The supporting materials are quite detailed to support readers who may wish to implement the method presented.

S1 Supplementary method

Here we present further specifications of datasets, followed by describing the multi-stage solution approach in detail. We then explain the preliminary analyses required before implementation of the approach to the study region.

S1.1 Datasets

To construct absolute sea-level (ASL) series from multi-mission altimeters, we considered additional geophysical and environmental corrections as listed in Table S1. We further applied the criteria shown in Table S2 to reduce the number of AXO series in the region.

Table S1 The remaining geophysical and environmental corrections applied to construct the mission-specific ASL time series.

Mission	Orbit	Sea state bias	Dry troposphere	Wet troposphere	Ionosphere
TOPEX	GSFC-Std1204	Chambers BM4-parametric	ECMWF	Radiometer	Smoothed dual-frequency
Jason-1	CNES-GDRE	CLS-nonparametric	ECMWF	Radiometer	Smoothed dual-frequency
OSTM/ Jason-2	CNES-GDRE	CLS-nonparametric-MLE3	ECMWF	Radiometer	Smoothed dual-frequency-MLE3
Jason-3	CNES-GDRE	CLS-nonparametric-MLE3	ECMWF	Radiometer	Smoothed dual-frequency-MLE3
ERS-2	GFZ-SLCCI-VER11	Gaspar BM3-parametric	ECMWF	Radiometer	NIC09
Envisat	CNES-GDRD	CLS-nonparametric	ECMWF	Radiometer	JPL-GIM
SARAL/ AltiKa	CNES-GDRE	NOAA-hybrid	ECMWF	Radiometer	JPL-GIM
Sentinel-3A	CNES-GDRF	Tran2012-nonparametric	ECMWF	Radiometer	Smoothed dual-frequency

Table S2 Root mean squared error (RMSE) and distance thresholds defined to reduce the number of AXO observations, for computational efficiency.

Crossover	Overflying missions	Threshold		# of observations
		RMSE (mm)	Distance (km)	
Tandem	TOPEX-side B & Jason-1	19	150	102
	Jason-1 & Jason-2	19	150	102
	Jason-2 & Jason-3	19	150	102
	ERS-2 & Envisat	35	200	105
Dual	ERS-2 & TOPEX-side A	84	350	134
	ERS-2 & TOPEX-side B	84	350	134
	ERS-2 & Jason-1	84	350	134
	Envisat & Jason-1	84	350	134
	Envisat & Jason-2	84	350	134
	SARAL & Jason-2	84	350	134
	Sentinel-3A & Jason-3	60	350	121

S1.2 Multi-stage solution approach

To cope with ill-posed nature of the problem, we offered the multi-stage strategy as summarized in Fig. 2 of the main paper, and here shown in Fig. S1 with more details. We commenced with “Solution 1” to attain a priori knowledge of mission-specific bias drifts, with the use of tight pseudo-observation constraints on nominal VLM rates at geodetic sites, treated them as linear quantities. In “Solution 2”, we refined our nominal VLMs, with respect to the derived estimates of time-fixed altimeter systematic errors. We subsequently ran “Solution 3” to simultaneously estimate potential time-variability in both bias drift and VLM parameters in a geocentric reference frame, imposed tight constraints on the linear components of VLM. Subsequently, we ran “Solution 2” to update the linear parts of VLM, with respect to the average estimates of the time-variable altimeter systematic errors.

S1.2.1 Solution 1

We commenced our multi-stage approach with “Solution 1” to derive a priori estimates of time-fixed bias drift per mission using a relatively tight process noise. We assumed zero-value as the initial bias drifts with large uncertainty. We imposed tight constraints on linear VLM at GPS and TG locations (from Hector trend and GPS-Krig analyses, respectively, see Sect. S1.3.1), and the nonlinear contributions of VLM were totally discarded. We treated intercepts of ATG and GPS series as time-variable quantities in the presence of a possible discrepancy between the a priori and actual values of VLM trend. To enhance the convergence and accuracy of the estimates, we iterated this solution, once the a priori estimates were updated based on the median estimates (for time-fixed variables) and the initial-epoch estimates (for the time-varying quantities). In the iteration, we tuned the process noise of time-variable intercepts in an adaptive fashion following the trends present in the ATG and GPS residuals (see a rule set given in Table S3).

S1.2.2 Solution 2

We followed with “Solution 2” to improve the a priori estimates of VLM trend, while tightly constrained to the median estimates of linear bias drifts from “Solution 1”, and the nonlinear VLM contributions were similarly discarded. We treated the intercepts as time-fixed variables from this solution onward to ensure proper modelling of the site-specific evolution of VLM. We updated the a priori estimates and repeated this solution, once the process noise of time-fixed VLMs were adopted from the trends present in the ATG and GPS residuals (see Table S3).

Table S3 Rule set proposed to adapt the process noise of time-variable intercepts, time-fixed VLMs, and time-variable VLMs following the trends present in the ATG and GPS residuals. Note s is the ~9.9-day Kalman timestep.

Residual trend bound (mm/year)		Intercept process noise (mm/ $\sqrt{s}$)	Linear VLM process noise (mm/year $\sqrt{s}$)	Nonlinear VLM process noise (mm/ $\sqrt{s}$)
Lower	Upper			
0	1	$1.089844/\sqrt{9.9}$	$0.001000/\sqrt{9.9}$	$0.871875/\sqrt{9.9}$
1	2	$1.174560/\sqrt{9.9}$	$0.003037/\sqrt{9.9}$	$0.939648/\sqrt{9.9}$
2	3	$1.259277/\sqrt{9.9}$	$0.007406/\sqrt{9.9}$	$1.007422/\sqrt{9.9}$
3	4	$1.335937/\sqrt{9.9}$	$0.010854/\sqrt{9.9}$	$1.068750/\sqrt{9.9}$
4	5	$1.423828/\sqrt{9.9}$	$0.013282/\sqrt{9.9}$	$1.139062/\sqrt{9.9}$
5	6	$1.545410/\sqrt{9.9}$	$0.016926/\sqrt{9.9}$	$1.236328/\sqrt{9.9}$
6	7	$1.657715/\sqrt{9.9}$	$0.020785/\sqrt{9.9}$	$1.326172/\sqrt{9.9}$
7	8	$1.742432/\sqrt{9.9}$	$0.024539/\sqrt{9.9}$	$1.393945/\sqrt{9.9}$
8	9	$1.822998/\sqrt{9.9}$	$0.027759/\sqrt{9.9}$	$1.458398/\sqrt{9.9}$
9	10	$1.903564/\sqrt{9.9}$	$0.030979/\sqrt{9.9}$	$1.522852/\sqrt{9.9}$

S1.2.3 Solution 3

In “Solution 3”, we sought to simultaneously estimate the time-variability in parameters of VLM and bias drift, with placing tight constraints on the median estimates of VLM rates generated from “Solution 2”. We used zero-value initial states, large uncertainties, and relatively loose process noise for altimeter systematic errors to capture any evolution induced by either mission-specific errors or common-mode TG VLMs (see Fig. S28). To compromise the differentiation between altimeter systematic errors and localized variability, we tuned the filter such that the dispersion of the weighted averaged stack of nonlinear VLMs at TGs per unit time closely matches that from the near coastal GPS sites (see Fig. 5). We assumed GPS heights were indicative of surface loading deformation, and we expected comparable nonlinearity at TG sites in spite of different spatial and temporal sampling of their networks around the continent.

We detected and excluded potential outlying ATG observations contaminated with substantial RSL datum issues (see Sect. S1.3.4). The “Solution 3” was then iterated once the process noise of nonlinear VLM was tuned to suitably separate the local-scale variability from mission-specific time-variable bias drifts (Table S3).

Having estimated the time-varying parameters of VLM and altimeter systematic errors, we subsequently ran “Solution 2” once more to update the VLM trends at TGs, relative to the weighted averages of time-variable bias drifts as the most probable values from “Solution 3”.

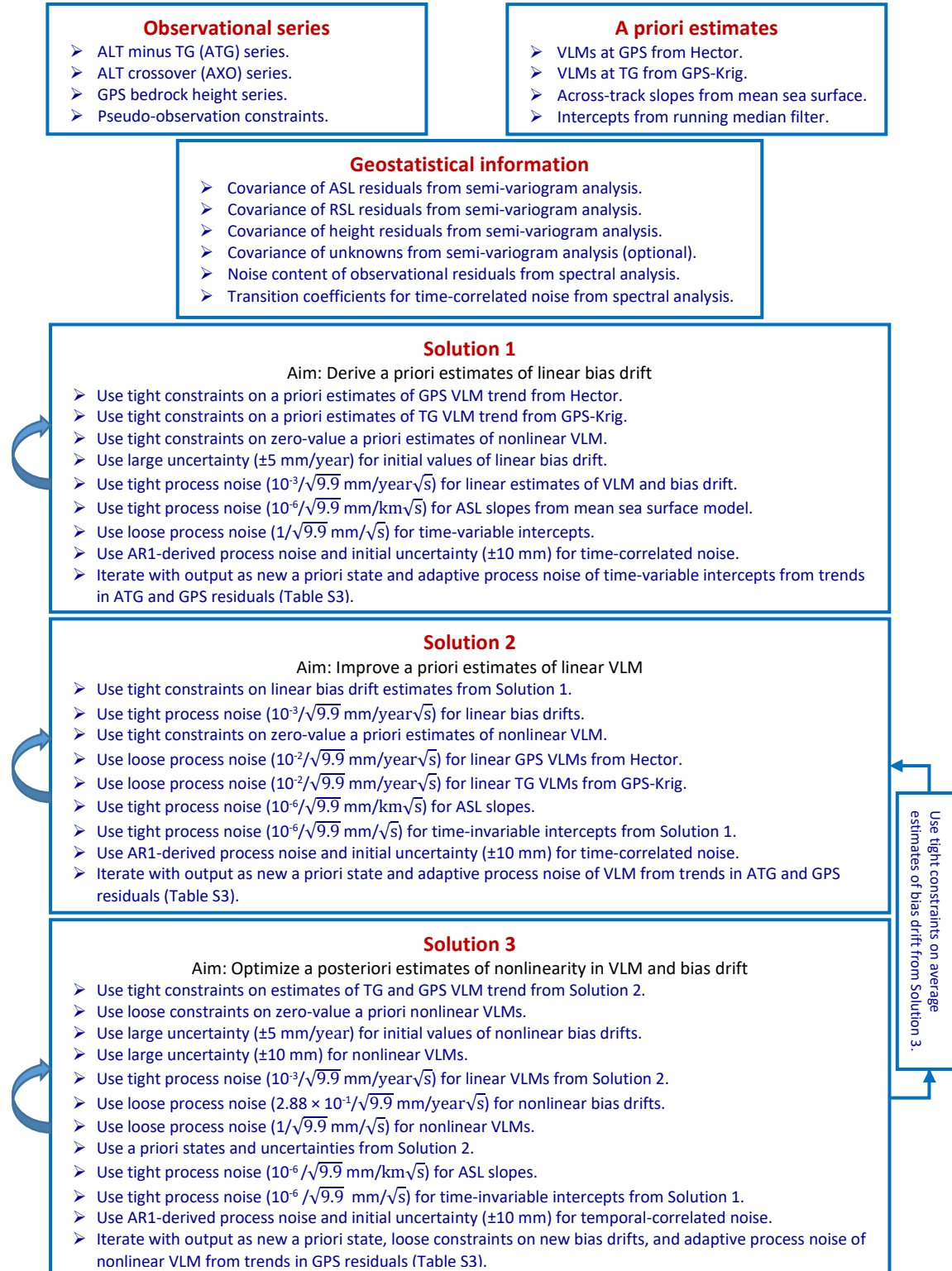


Fig. S1 A flow illustration of multi-stage implementation strategy to estimates unknowns in an iterative manner. The solutions commenced with deriving a priori estimates of linear bias drifts using a priori knowledge about linear VLMs at TG sites, then rectified a priori linear VLMs, and concluded with simultaneous estimates of time-variability in bias drift and VLM parameters in the same reference frame.

We derived a priori estimates of across-track ASL slope at the multi-mission CPs from the DTU15 mean sea surface (MSS) model as a function of the zonal-track distances (as per Rezvani et al. 2021), and these parameters were tightly constrained to the medians of a posteriori estimates from the former solutions subsequently. We modelled the correlated noise with zero initial value and large uncertainty, and the process noise was adopted from power spectrum analysis of respective residuals (Sect. S1.3.2).

The AXO intercepts, determined from the medians of the observational series, were similarly introduced as tight constraints to assist in retrieving linear altimeter systematic errors in conjunction with the ATG observations in all solutions, except for the last optimization where these were updated given nonlinear estimates of bias drift.

Our computations (based on 1560 ATG, and 1336 AXO, and 210 GPS observations) were processed on two nodes each with 28 available CPUs (with clock speed well under contemporary Intel Xeon frequencies) and 128 GB of memory, which required 7.48 (7.16), 8.88 (6.87) and 14.04 (13.56) hours for Solutions 1, 2 and 3 (and the respective iterations in brackets), respectively.

S1.3 Preliminary analyses

Below we consecutively present the preliminary analyses to determine (i) a priori VLM at TG locations from GPS-Krig approach, (ii) noise content of time-variant and time-invariant errors in the observational series, and (iii) covariances within each set of observations. The ability to detect potential datum errors is also investigated.

S1.3.1 GPS-Krig VLM at TG locations

We first estimated the regional velocity field at GPS locations through the trend estimation process within the Hector software version 1.6 (Bos et al. 2013), along with instrumental offsets (where they existed) as well as annual and semi-annual signals given a “white plus power-law” noise model (Williams et al. 2004). We then estimated the a priori VLM at TG locations from GPS-Krig interpolation of the Hector-inferred GPS velocity within 150 km. Following the approach presented by Rezvani et al. (2021), we applied the generalized least squares to Universal Kriging models to estimate the unknowns of TG VLM trend using the observations of the nearby GPS VLM rates (see Table S4). Within this process, the nearby GPS VLM rates were weighted according to the nominal variances from Hector analysis as well as the added variances as a function of the separations

between TG and GPS locations. The latter term is required as we did not directly observe VLM at TG locations and the uncertainty of VLM errors should be increased as distancing from each GPS site. Further details about the GPS-Krig interpolation can be found in Text S1.4.1 of Rezvani et al. (2021).

S1.3.2 Spectral noise analysis

We used Lomb-Scargle power spectra of observational residuals (after removal of linear fit, Fig. S2) to determine the noise content at measuring locations in terms of time-dependent and time-independent errors (e.g., Buttkus 2000). We approximated time-correlated noise of observations to the first-order autoregressive (AR1) sequence and defined the “white plus AR1” stochastic model for the ATG, dual AXO and GPS, but a “white-only” model for the tandem AXO series. We assumed the residual oceanography between the TG and CP measurement locations as a stationary process over the satellite era, and the time-correlated noise were thus estimated by stacking ATG combinations from all missions overflying a specific CP.

Within this process, we specified variances of time-independent noise populated in the diagonal terms of the ATG $\mathbf{R}(\mathbf{e}^{\text{ATG}}) \equiv \mathbf{R}(\mathbf{e}_q^{\text{ATG}})$, AXO $\mathbf{R}(\mathbf{e}^{\text{AXO}}) \equiv \mathbf{R}(\mathbf{e}_q^{\text{AXO}})$ and GPS $\mathbf{R}(\mathbf{e}^{\text{GPS}}) \equiv \mathbf{R}(\mathbf{e}_q^{\text{GPS}})$ covariance matrices. We further determined magnitudes of time-dependent noise (populated in the diagonal elements of the $\mathbf{Q}(\boldsymbol{\varepsilon}^\xi) \equiv \mathbf{Q}(\boldsymbol{\varepsilon}_q^\xi)$ VCV matrix), in conjunction with the AR1 correlation coefficients (populated in the relevant elements of the diagonal $\mathbf{F}$ transition matrix). The remaining elements in the transition matrix defined the temporal evolution of parameters through random-walk processes as described in Fig. S1. Further details can be found in Text S1.4.2 of Rezvani et al. (2021).

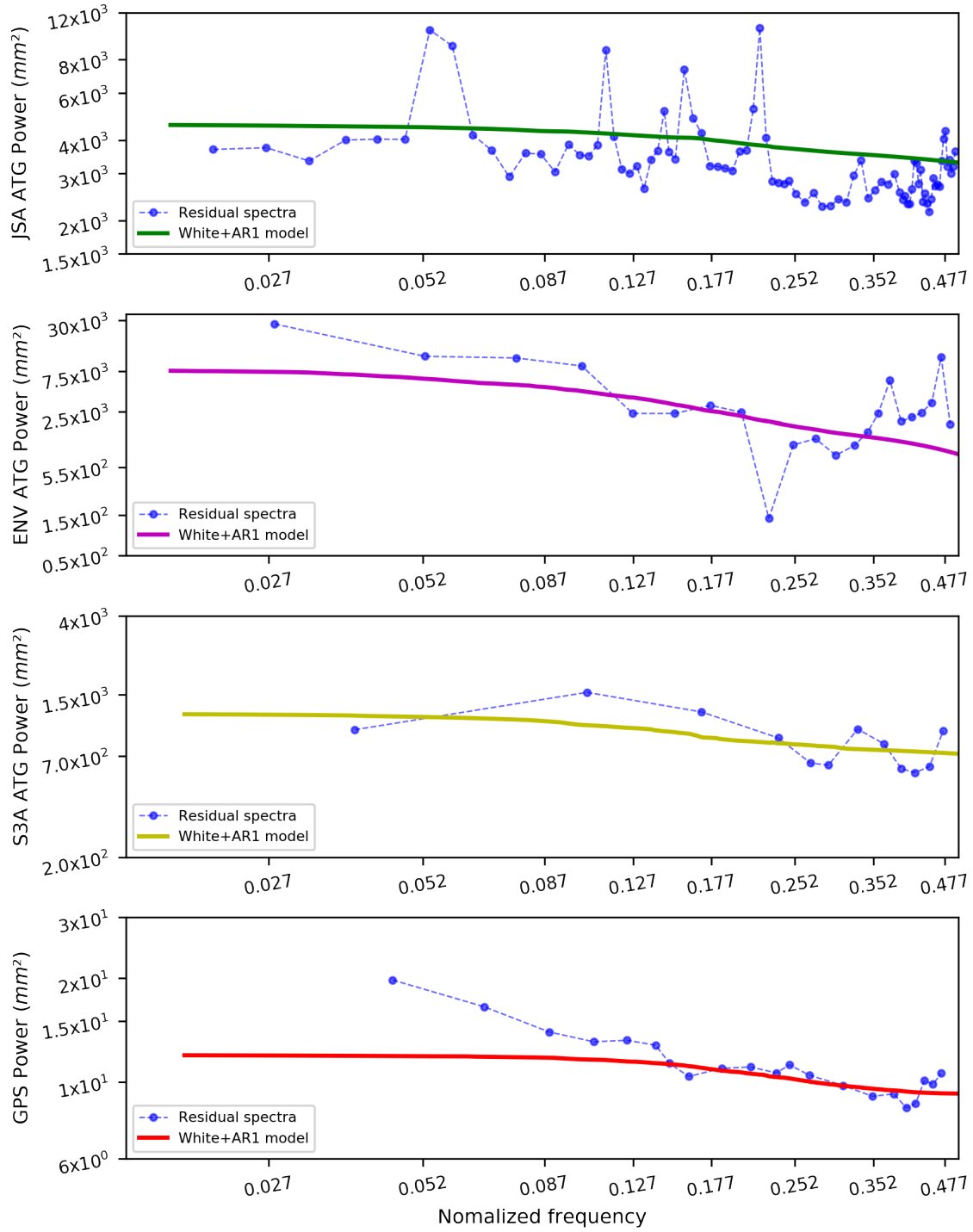


Fig. S2 Median power spectral density of input dataset for (top) ATG in the case of (top row) Jason-series, (second row) Envisat-series, and (third row) Sentinel-3A, and for (bottom row) GPS height observations. Note the “white plus AR1” noise model is a quite reasonable fit to the ATG observations, yet the peaks indicate the presence of residual tides. This model slightly underpredicts the low-frequency energy in the GPS observations at the low-frequency end.

S1.3.3 Semi-variogram analysis

We used the semi-variogram analysis to determine the similarity between adjacent samples in the random fields varying across time and space (e.g., Montero et al. 2015). We first computed empirical semi-variances of observational residuals of ASL, RSL and GPS height that were measured at paired locations. We subsequently extracted the spatiotemporal covariances from Gaussian negative-definite semi-variogram models fitted to the resultant semi-variances at temporal slices up to 10 days (Fig. S3). We further computed the covariances within ATG and AXO noise by propagating random errors. We populated these in the off-diagonal elements of the ATG $R(e^{\text{ATG}}) \equiv R(e_q^{\text{ATG}})$, AXO $R(e^{\text{AXO}}) \equiv R(e_q^{\text{AXO}})$, and GPS $R(e^{\text{GPS}}) \equiv R(e_q^{\text{GPS}})$ covariance matrices up to the length scales of 750, 750 and 350 km, respectively. Further details can be found in Text S1.4.3 of Rezvani et al. (2021).

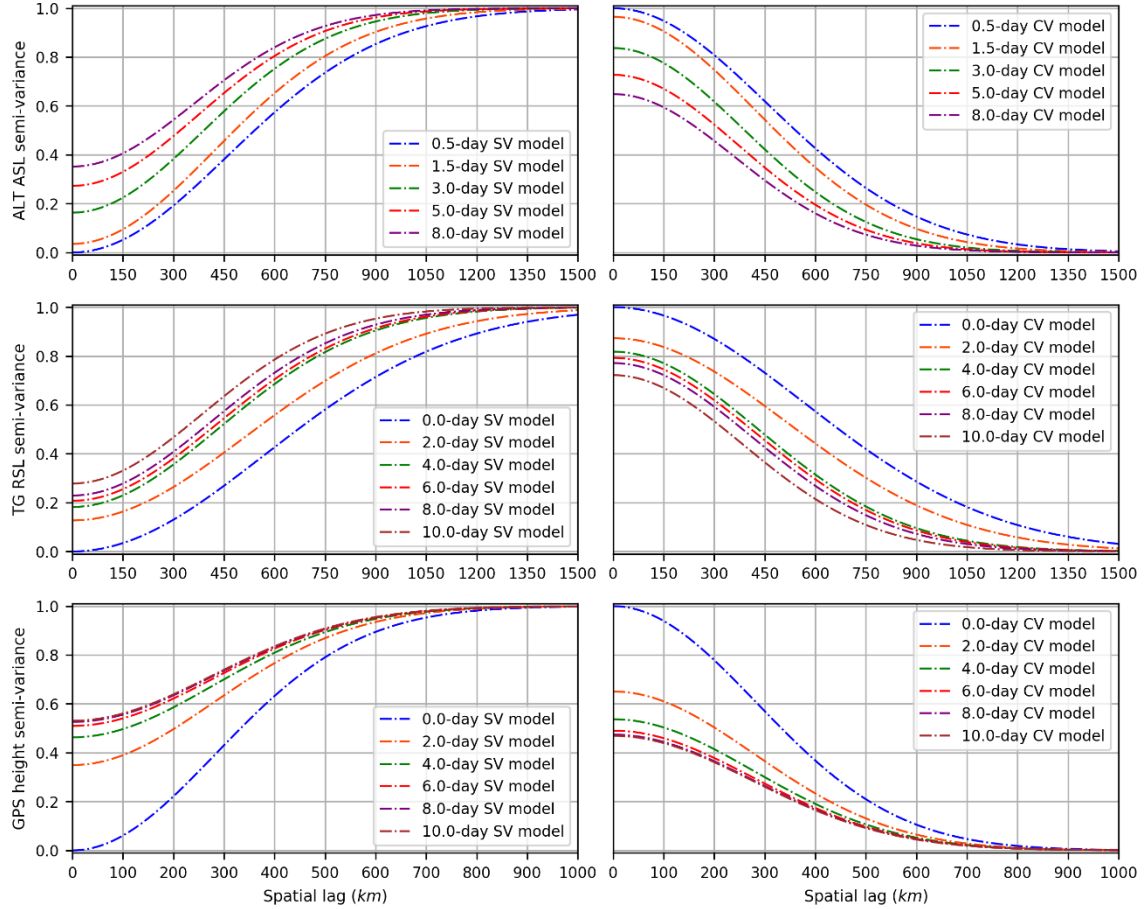


Fig. S3 Gaussian negative-definite semi-variograms (SV, left panel) and positive-definite co-variograms (CV, right panel) with models derived from semi-variances of the residuals of (top) ALT ASL, (middle) TG RSL and (bottom) GPS height around the Australian region. Note the nugget effects are relative to the semi-variance estimates at zero-lag in space and time.

S1.3.4 TG datum errors detection

The presented method had the ability to detect potential datum errors in the relative sea-level (RSL) records, and subsequently mitigated the unfavourable impacts on our estimates of VLM and bias drift. This process involved visually checking cycle-by-cycle weighted averages of “white plus AR1” ATG residuals on a per TG basis (i.e., these were stacked from all CPs relevant to any given TG in the solutions). Any significant nonlinear behaviour, in comparison with those from nearby TGs as well as the residual “stack” analysis shown in Fig. 12 of the main paper, could create the possibility of datum errors. For instance, Fig. S4 shows a datum shift uncovered from the analysis of ATG residuals pertaining to the TG at STONY POINT (STON) location.

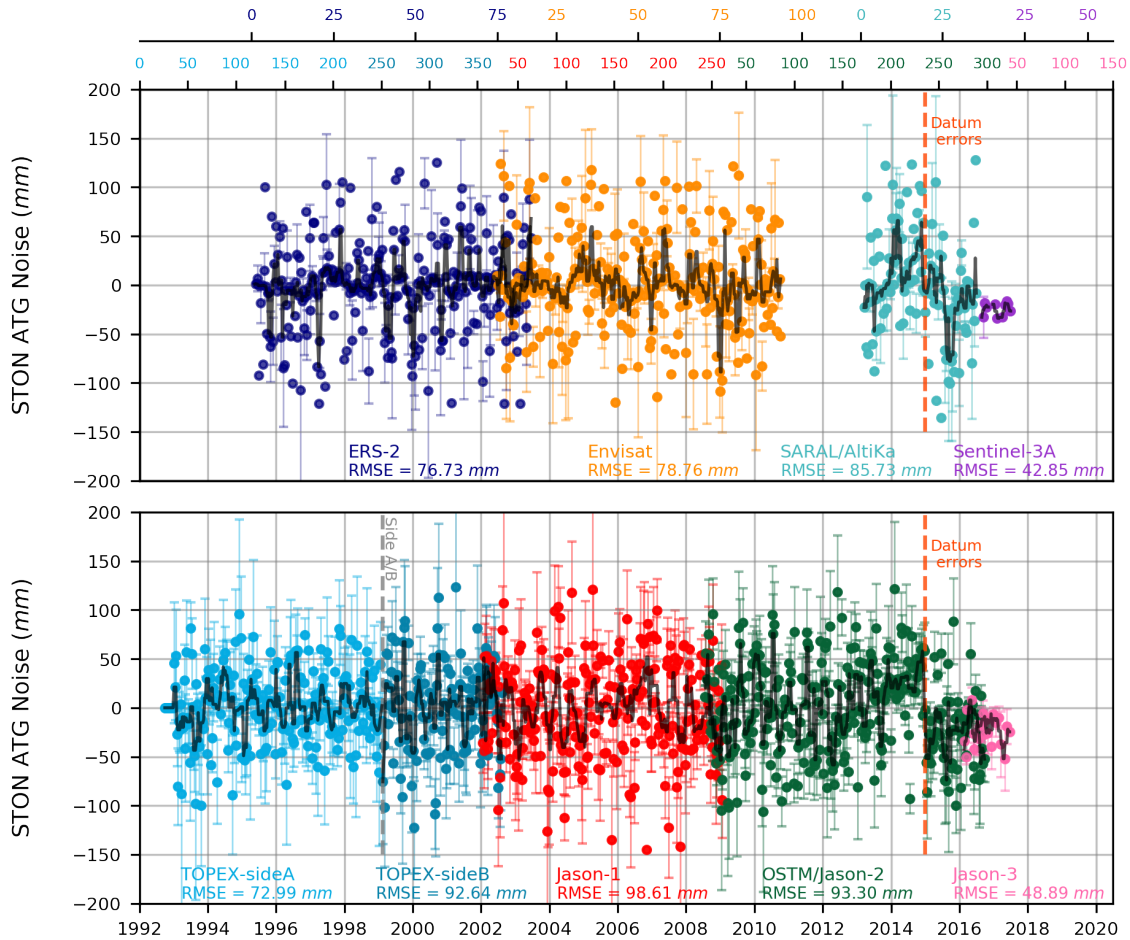


Fig. S4 Uncovered datum errors of $\sim \pm 35$ mm in RSL data recorded at STON gauge location affecting the ALT and TG observations since ~ 2015 , that were detected using cycle-by-cycle weighted average of the “white plus AR1” ATG residuals. The dashed orange lines specify the temporal margins of these datum shifts.

S2 Supplementary results

We here show complementary results to those presented in the main paper. First, we compare our estimates VLM trend at TGs with the ICE6G_D GIA predictions (Peltier et al. 2018). Second, we explore the weighted average stacks of nonlinear VLMs at regional scales, and evaluate the consistency between nonlinear VLM estimates at TG and GPS sites. Third, we estimated relative biases to ensure the consistency of the sea-level records by multi-mission altimeters. Fourth, we investigated the spatial coherence of ASL at TG locations using VLM trends derived from the GPS-Krig approach and GIA model. Further, we undertook a suite of sensitivity tests to evaluate the reliability of our VLM, ASL and bias drift estimates, and the potential presence of geophysical and oceanographic signals in our estimates. We subsequently focused on the potential presence of differential oceanography as a function of distances of the altimeter measurement locations from the TGs and coast, followed by assessing residuals and a posteriori analysis.

S2.1 VLM estimates

S2.1.1 Linear VLM

Figures 3 and 4 in the main paper compare our estimates of VLM trends with those derived from the spatially interpolated GPS-Krig rates. Here, Fig. S5 shows the differences between our VLMs and predictions from the ICE6G_D GIA model, and the latitudinal profile of these differences are shown in Fig. S6. Note that in these figures we flagged by cyan labels those gauges specified with the significant differences (1-sigma) between our VLM and GIA trends. Also, the error bars are ± 1 -sigma uncertainties of the VLM differences, have been scaled by the a posteriori variance factor, and assumed a nominal uncertainty of ± 1 mm/year for the GIA predictions.

Figure S7 shows our estimates of VLM uncertainty in compared with those from GPS-Krig and Hector-based solutions, at TG and GPS sites, respectively. We derived our uncertainties at ± 1 -sigma level, which have been scaled by the a posteriori variance factor.

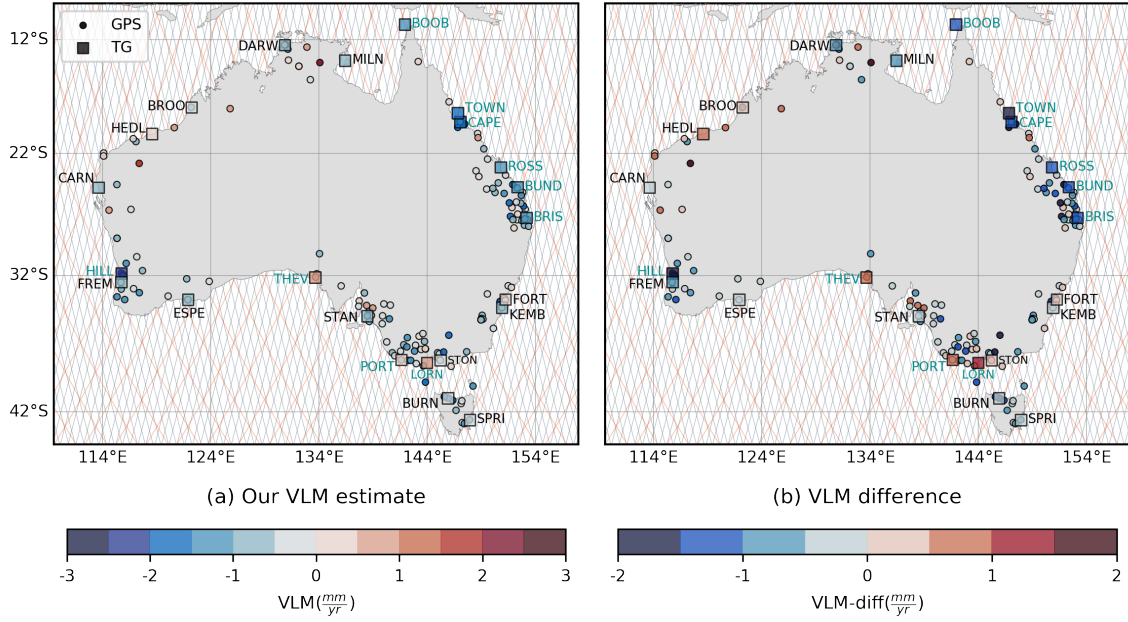


Fig. S5 Map of (a) our estimates of time-fixed VLMs, and (b) differences of our approach minus ICE6G_D GIA at tide gauges (TGs, squares) and GPS sites (circles). TGs with significant differences at 1-sigma are annotated in cyan. For clarity, TG latitude at TOWN and FREM locations are shifted by +0.75 and -0.45 degrees, respectively. The ground tracks of Jason-series and Envisat-series altimeters are shown in orange and grey, respectively. Note the different colour scales in (a) and (b).

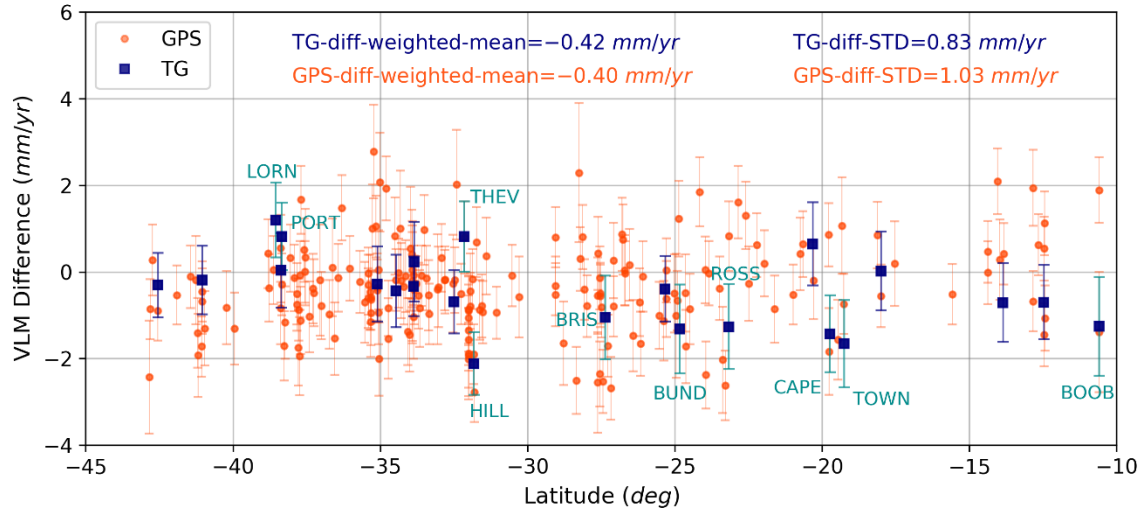


Fig. S6 Profile of differences in time-fixed VLM plotted against latitude, our estimates minus ICE6G_D GIA rates at TGs (blue squares) and GPS sites (orange circles). TGs with significant differences at 1-sigma are annotated in cyan. Error bars are ± 1 -sigma and scaled by the a posteriori variance factor. For clarity, TG latitudes at CAPE, CARN and FREM locations are shifted by -0.45 degrees, respectively.

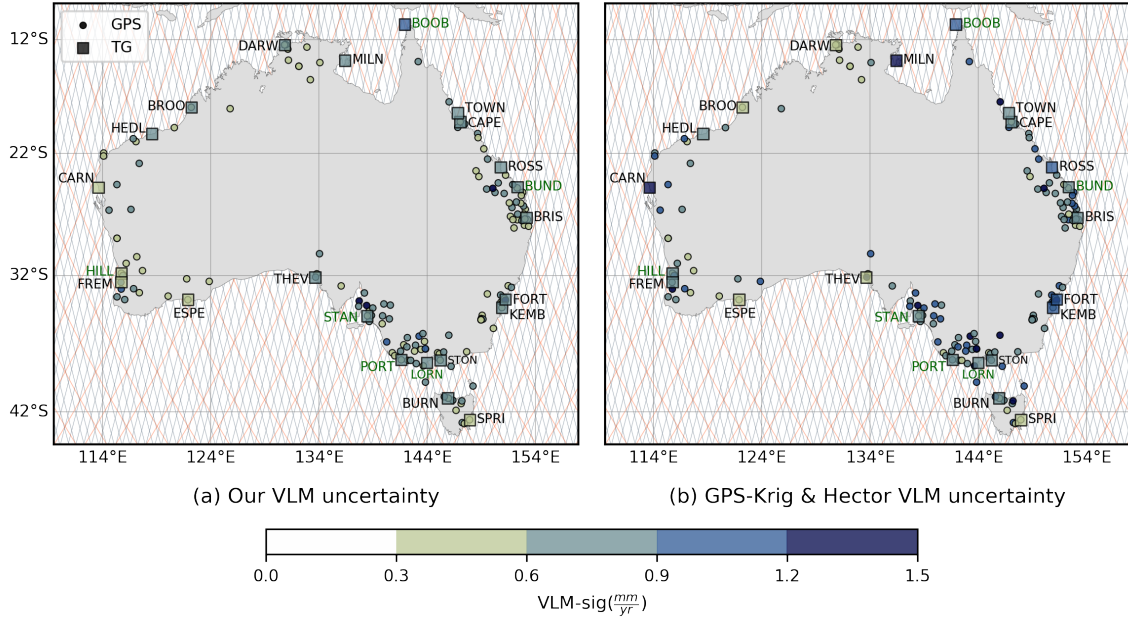


Fig. S7 Map of (a) our VLM uncertainty estimates, scaled by a posteriori variance factor, against (b) those from GPS-Krig at TGs and Hector analysis at GPS sites. The ground tracks of Jason-series and Envisat-series altimeters are shown in orange and grey, respectively.

S2.1.2 Nonlinear VLM

We next sought to examine the fidelity of our approach to resolve potential time-variability in site-specific VLMs. Figure 5 in the main paper compares the weighted average stack of our nonlinear VLM estimates inferred at TG and GPS locations around the Australian region. Here, Figs. S8-S11 compare the weighted average stacks of our nonlinear VLMs at geodetic sites in the NW, SW, SE, and NE sub-regions. The annotated standard deviations (STDs) on these figures indicate the comparable variability between these stacks.

Our further investigations reveal that the stacks of nonlinear TG VLMs are correlated with the ENSO variability with the magnitudes of -0.26 , -0.11 , -0.08 and -0.19 in the NW, SW, SE, and NE sub-regions, respectively. These comparisons better reveal the potential link between ENSO and the nonlinear VLM estimates at regional scales, as compared to the coastal-wide TG stack around the study region shown in Fig. 5. The big challenge here is that we expect the biggest hydrology signal in VLM in N/NW sites - we also potentially expect the biggest contribution of ENSO to ATG records - e.g., steric signal over deep water will be ENSO-related and this only partially reaches the TG. This is highly challenging to quantify, and it may well be the limit of how we separate the TG and ALT signals.

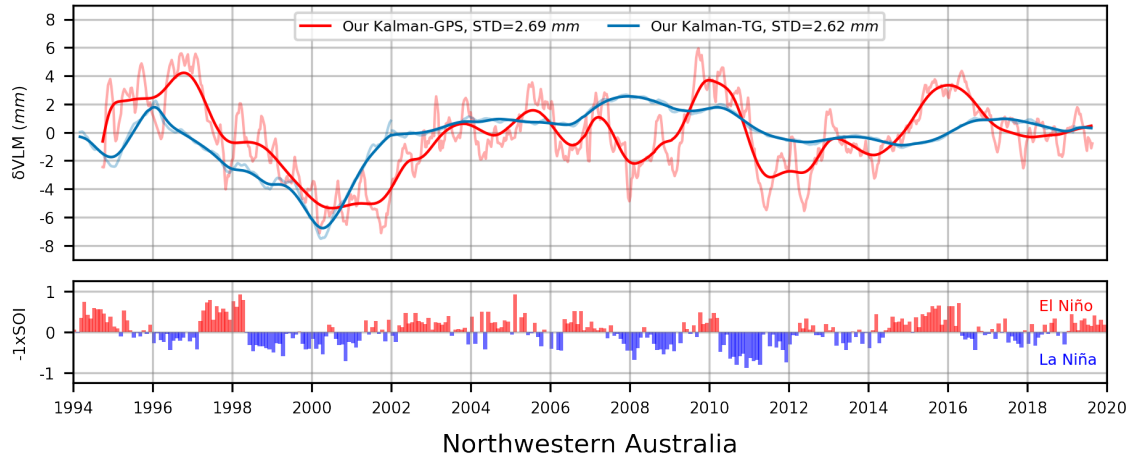


Fig. S8 Weighted average stack of our estimates of time-variable VLMs at tide gauges (TGs, blue line) and coastal Global Positioning System (GPS) sites (red line) from Solution 3 in the NW sub-region. The smoothed lines show the low-passed results after applying a Butterworth filter to the stacked series, showing comparable variability of hydrological loadings. For comparison, Southern Oscillation Index (SOI) with the sign reversed is shown in the lower panel as the climatic descriptor in the region. The standard deviations (STDs) of the stacked series are annotated.

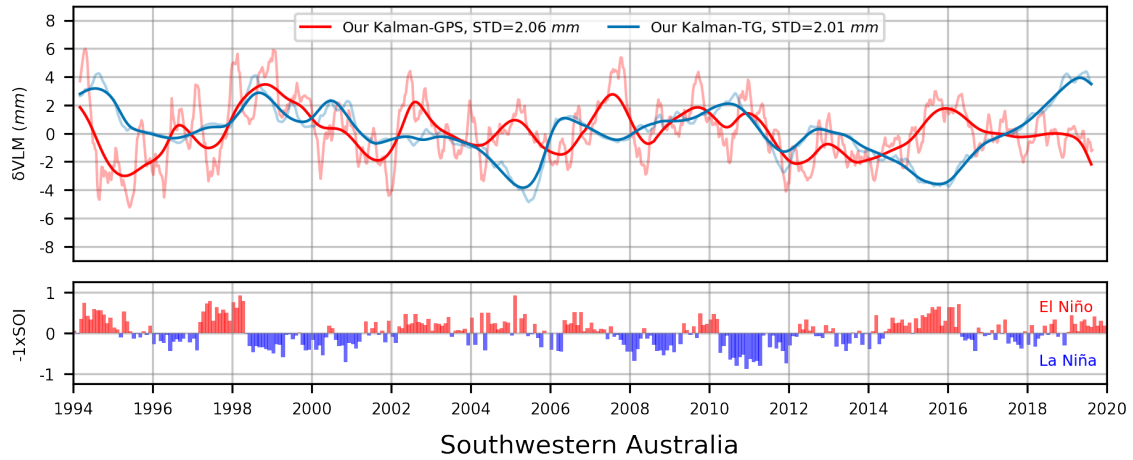


Fig. S9 Same as Fig. S8, but for the SW sub-region.

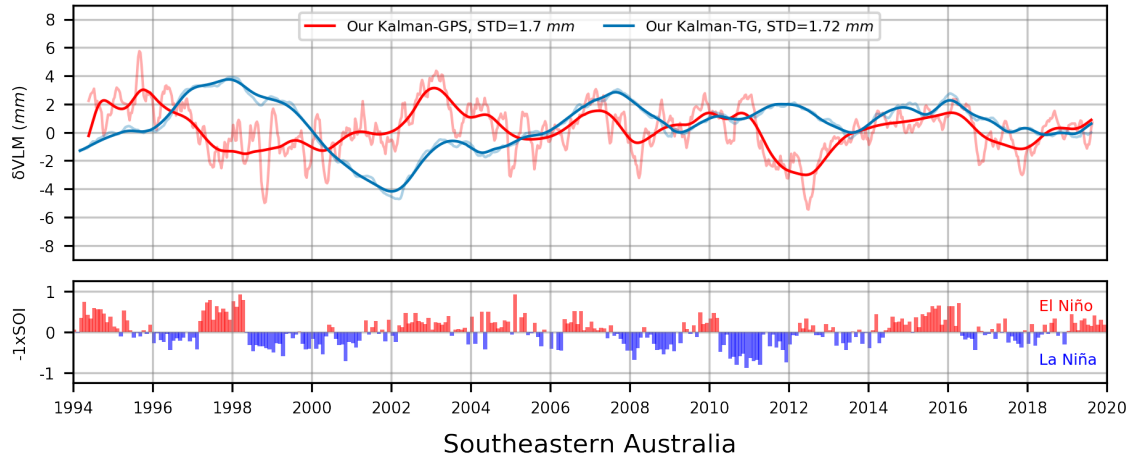


Fig. S10 Same as Fig. S8, but for the SE sub-region.

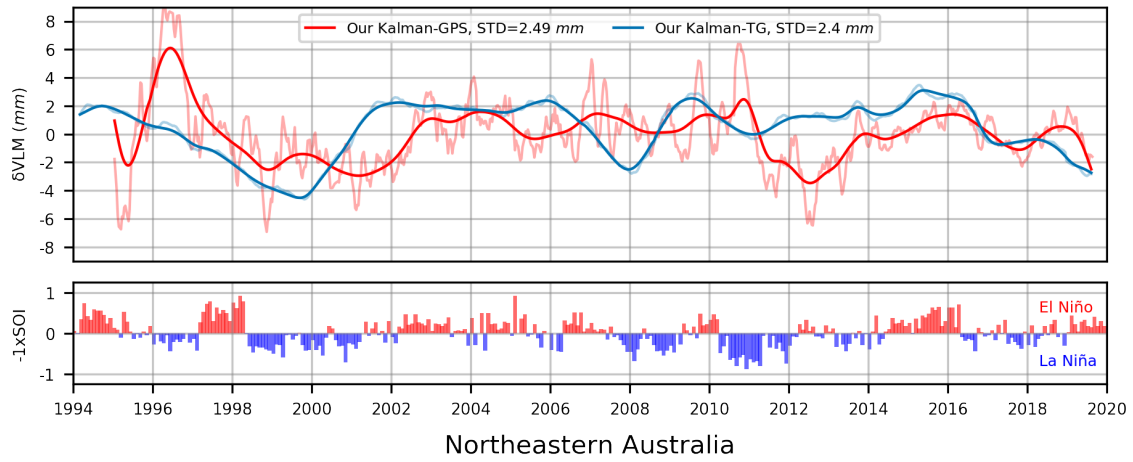


Fig. S11 Same as Fig. S8, but for the NE sub-region.

We further investigated our estimates of nonlinear VLMs at the TGs and nearby GPS sites, on a case-by-case basis. Figures S12-S16 show the site-by-site comparisons between the nonlinear VLM estimates between GPS and TG sites in the NW, SW, SE, and NE sub-regions, respectively.

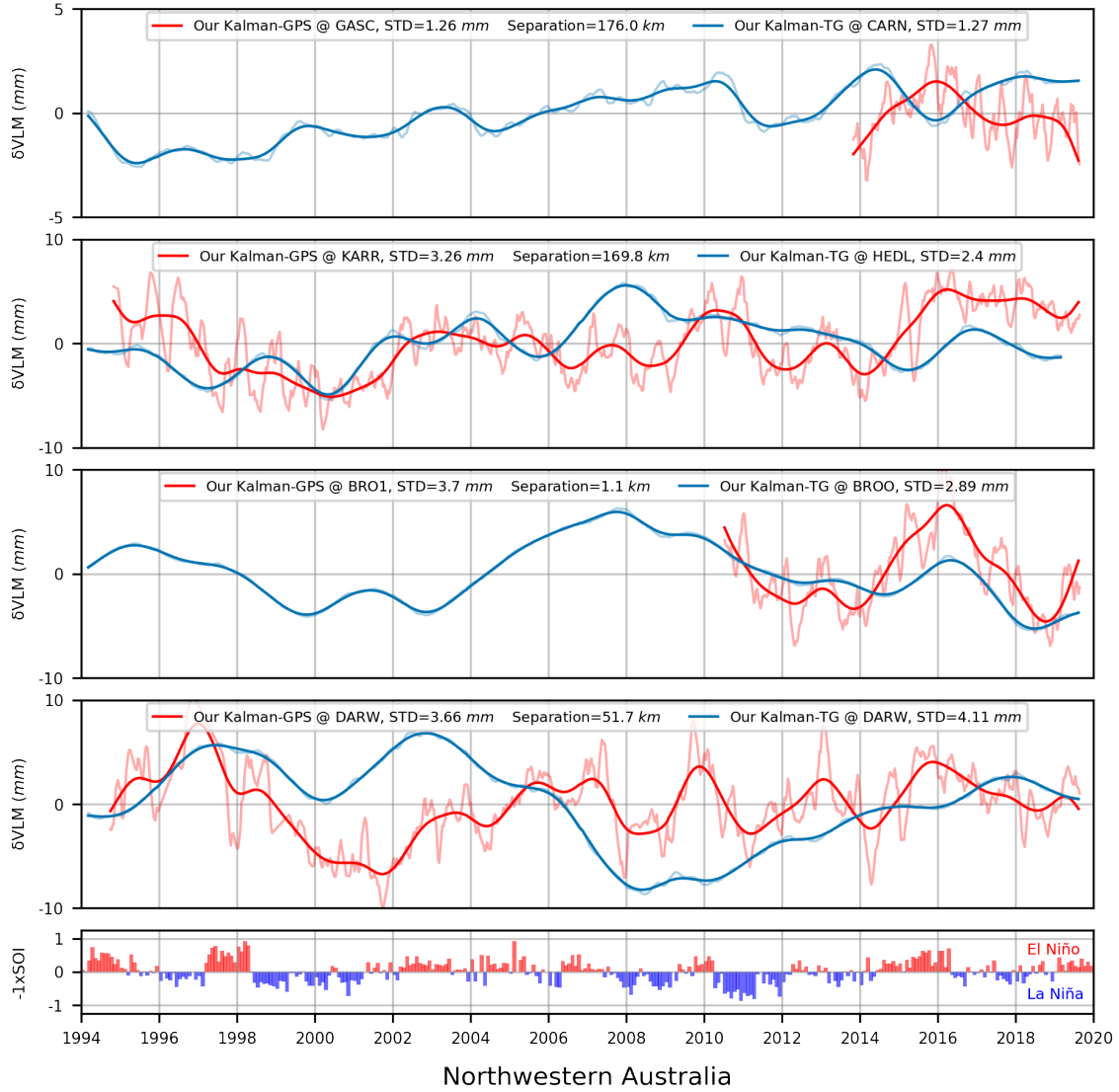


Fig. S12 A site-by-site comparison between nonlinear VLMs at TGs and nearby GPS sites in the NW sub-region. The smoothed lines show the low-passed results after applying a Butterworth filter to the stacked series, showing comparable variability of hydrological loadings. For comparison, Southern Oscillation Index (SOI) with the sign reversed is shown in the lower panel as the climatic descriptor in the region. The standard deviations (STDs) of the localized variabilities and the separations between each TG and nearby GPS are annotated.

These comparisons show the high variability between GPS- and TG-specific estimates of nonlinear VLM, due to the spatial separation, the ENSO-related effects, and the technique-specific errors. Overall, these site-by-site inspections suggest the presence of the oceanographic and geophysical signals in the estimates of nonlinear VLM at the TG locations, especially in the areas with complex geometry.

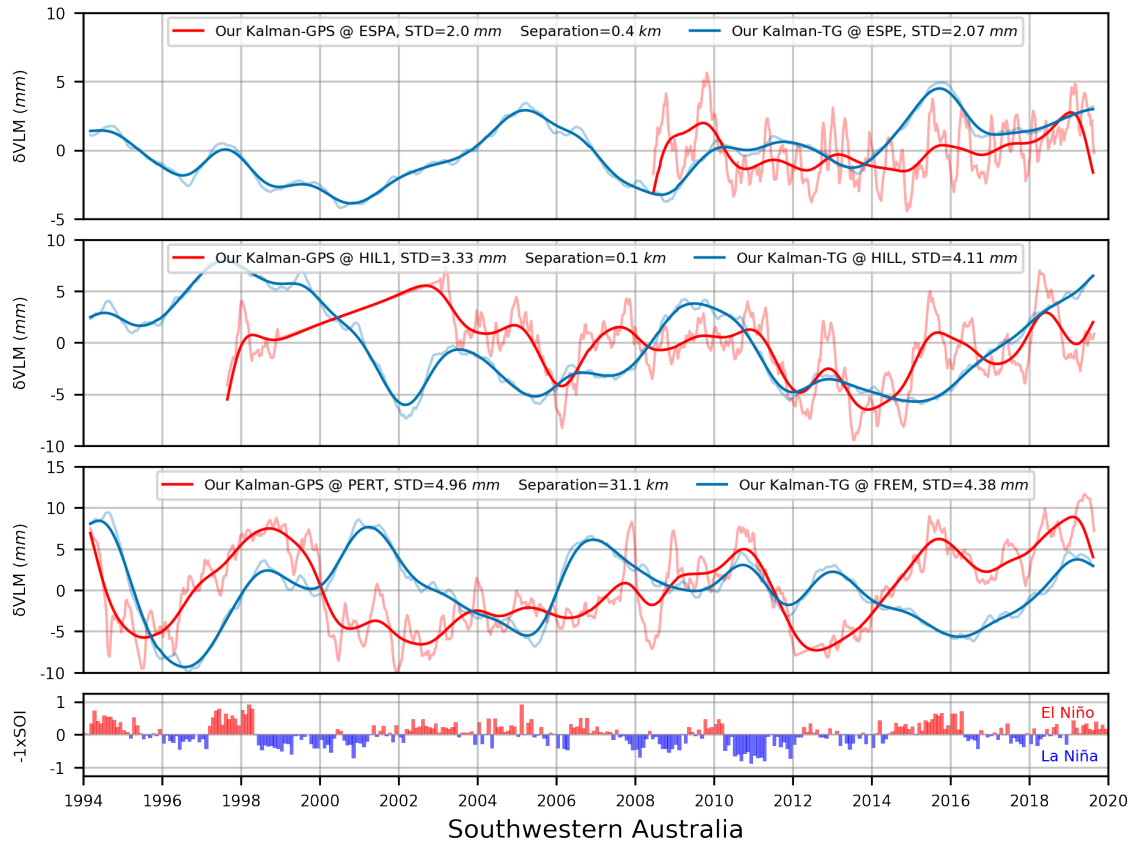


Fig. S13 Same as Fig. S12, but for the SW sub-region.

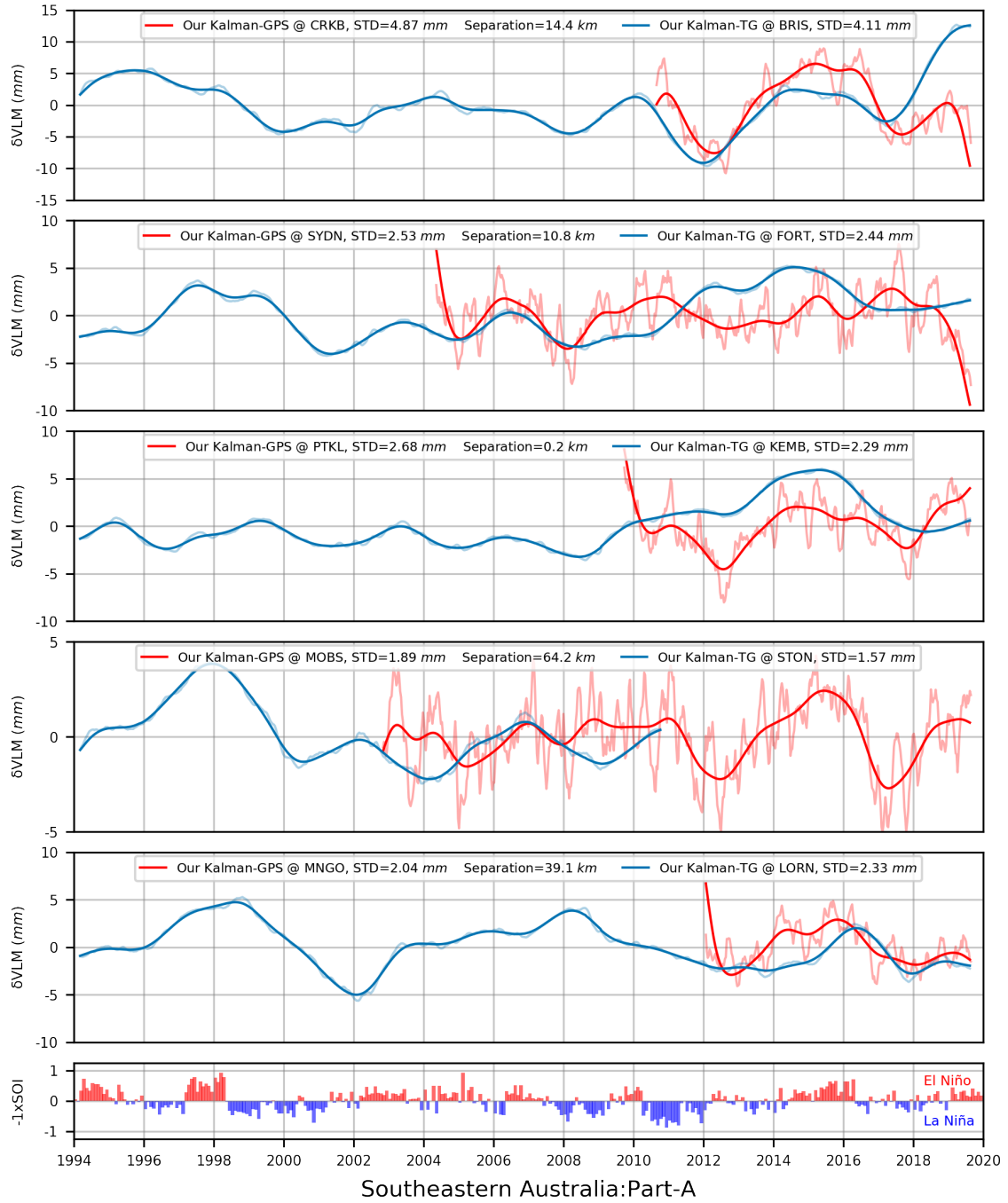


Fig. S14 Same as Fig. S12, but for the SE sub-region, Part-A.

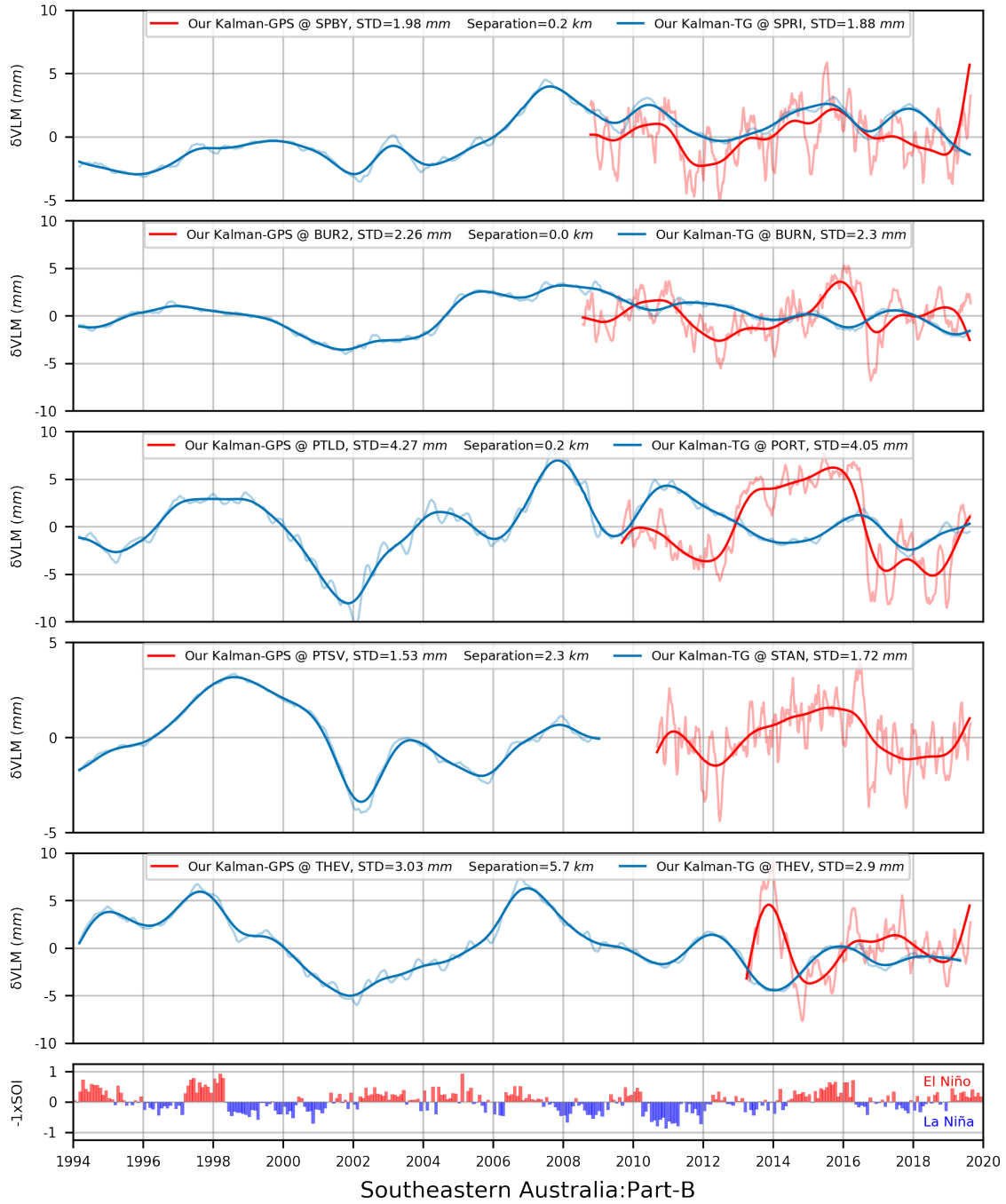


Fig. S15 Same as Fig. S12, but for the SE sub-region, Part-B.

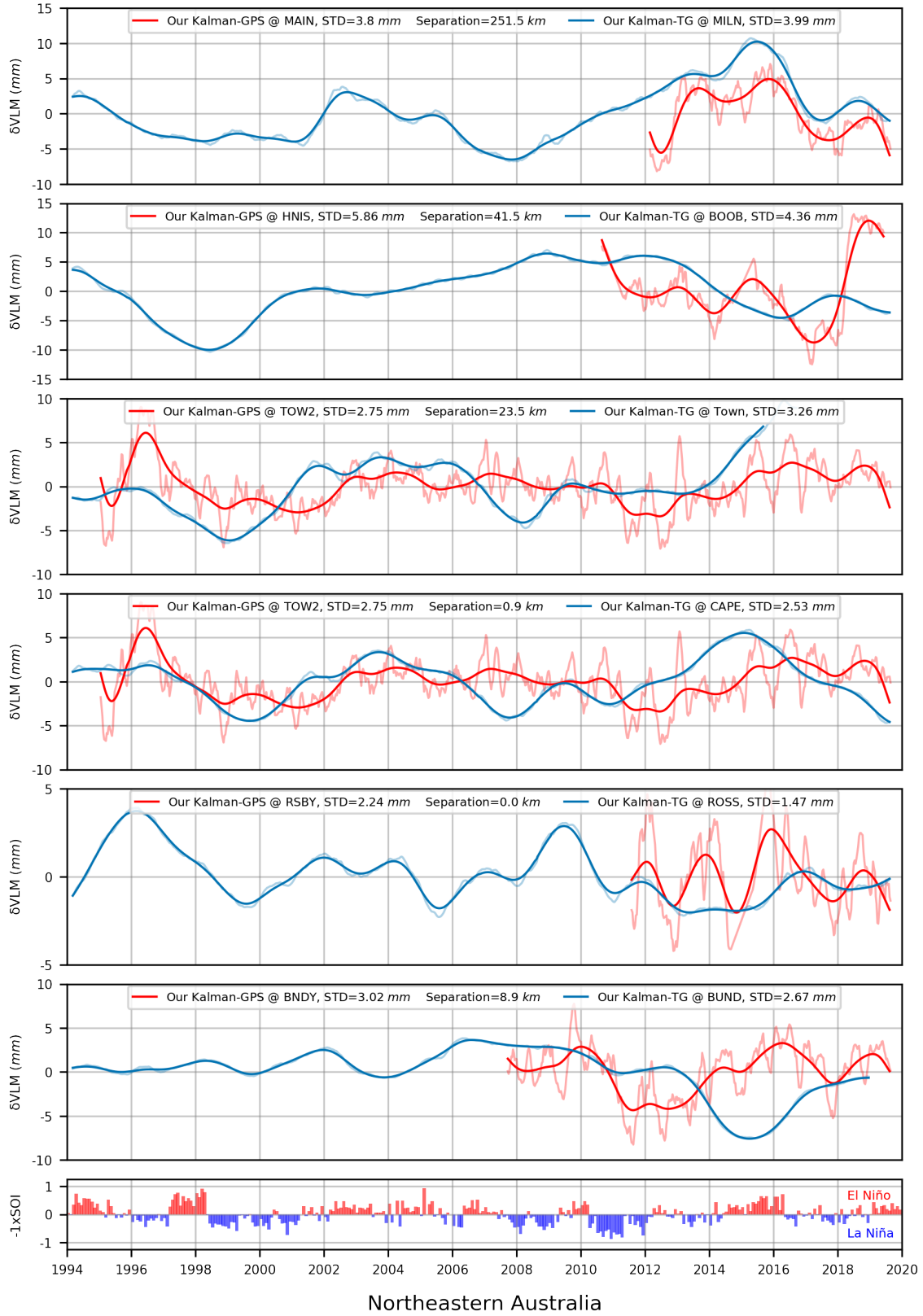


Fig. S16 Same as Fig. S12, but for the NE sub-region.

S2.2 Altimeter relative bias estimates

Figure 6 in the main paper shows our estimates of time-variable systematic errors of the altimeter records around the Australian region. Here, Figs. S17 and S18 show our estimates of inter-mission and intra-mission biases between the consecutively launched altimeters as a function of latitude. These relative values are essential to ensure the consistency of the sea-level series recorded across multi-mission lifespans (e.g., Nerem et al. 2010). To check the internal consistency, we therefore compared the estimates of inter-mission bias from the dual and tandem crossovers versus those from the ATG differences, except for the TOPEX-side A/B intra-mission bias that was merely determined using the resultant ATG intercepts.

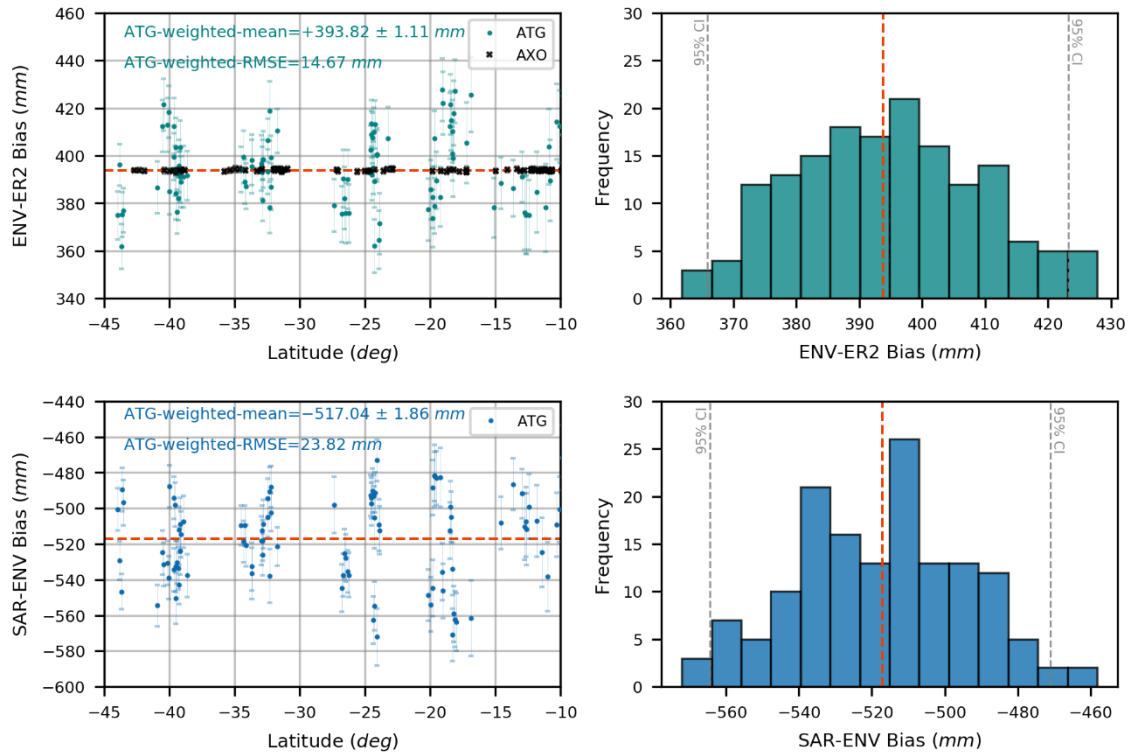


Fig. S17 Intra and inter-mission relative biases of (top row) Envisat (ENV) minus ERS-2 (ER2), and (bottom row) SARAL (SAR) minus Envisat (ENV) at altimetry CPs derived from estimated intercepts of altimeter minus tide gauge (ATG) and tandem altimeter crossover (AXO) observations. Left panels compare profiles of ATG and AXO biases by latitude, and right panels show histograms of the ATG-only relative biases. The relative biases from the AXO tandem intercepts are shown with black crosses in the left panels (absent in the bottom row given no formation flight between ENV and SAR missions). The orange dashed lines show the most probable values of the intra- and inter-mission biases. The weighted average and weighted root mean squared error (WRMSE) of the location-specific estimates are annotated. Note the different scales on y-axes.

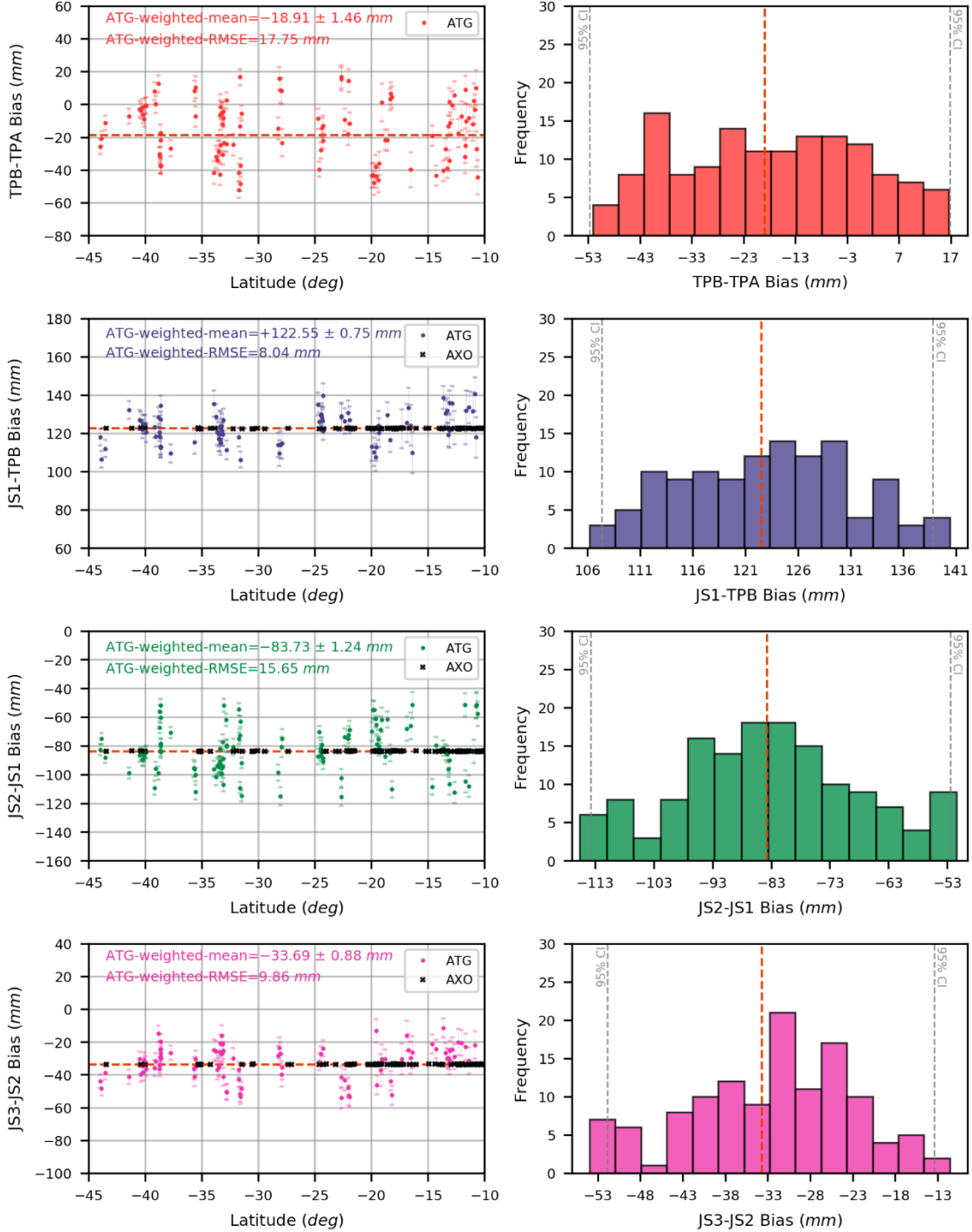


Fig. S18 Intra and inter-mission relative biases of (top row) TOPEX-side B (TPB) minus TOPEX-side A (TPA), (second row) Jason-1 (JS1) minus TOPEX-side B (TPB), (third row) Jason-2 (JS2) minus Jason-1 (JS1), and (bottom row) Jason-3 (JS3) minus Jason-2 (JS2) at altimetry CPs derived from estimated intercepts of altimeter minus tide gauge (ATG) and tandem altimeter crossover (AXO) observations. Left panels compare profiles of ATG and AXO biases by latitude, and right panels show histograms of the ATG-only relative biases. The relative biases from the AXO tandem intercepts are shown with black crosses in the left panels (absent in the top row given no formation flight between TPA and TPB missions). The weighted average and weighted root mean squared error (WRMSE) of the location-specific estimates are annotated. The orange dashed lines show the most probable values of the intra- and inter-mission biases. Note the different scales on y-axes.

S2.3 Implications for coastal and offshore ASL

Figure 7b in the main paper shows our estimates of ASL rates at TG locations around the Australian coast. For comparison, here Fig. S19 shows the ASL rates at TGs inferred from the GPS-Krig and GIA alternatives. We inferred an improved coherence of our ASL trends at the adjacent TGs around the region, compared to those based on the GPS-Krig and GIA VLM rates.

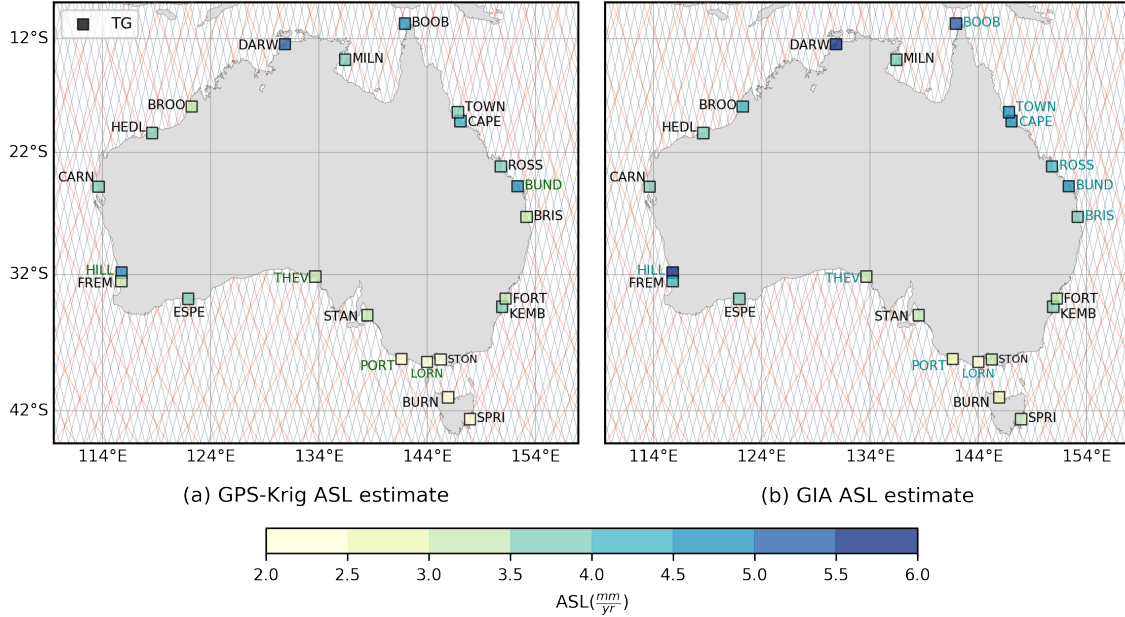


Fig. S19 Map of ASL at TG locations resulted by applying linear VLMs from (a) GPS-Krig, and (b) ICE6G_D model to the RSL trends in the same timeframe. TGs with 1-sigma significant differences of our VLMs minus GPS-Krig and GIA are annotated in green and cyan in the left and right, respectively. For clarity, TG latitude at TOWN and FREM locations are shifted by +0.75 and -0.45 degrees, respectively. The ground tracks of Jason-series and Envisat-series altimeters are shown in orange and grey, respectively.

To examine the spatial variability in absolute sea-level rise, as shown in Fig. S20, we further fitted a quadratic polynomial to the underlying sets of the ASL estimates as a function of reduced latitudes, i.e., the latitudes in the SE-NW direction. From this figure, our VLM estimates led to reducing the root mean squared error (RMSE) of the fitted polynomial, in contrast to the GPS-Krig and GIA values.

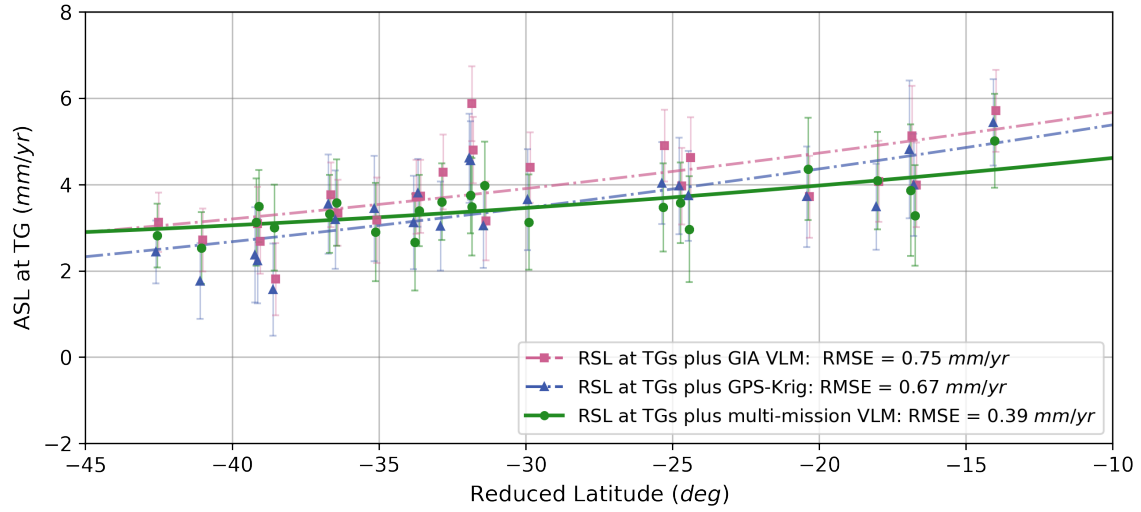


Fig. S20 Profile of absolute sea-level (ASL) trends at tide gauges (TGs), comparing estimates derived using relative sea-level (RSL) plus our multi-mission VLMs (green circles) with those from Global Positioning System (GPS)-Krig (blue triangles) and ICE6G_D Glacial Isostatic Adjustment (GIA, pink squares) values. Solid and dashed lines show a quadratic polynomial fitted to each set of ASL estimates per latitude reduced to the SE-NW direction with root mean squared error (RMSE) about this fit annotated in the legend. Error bars are ± 1 -sigma scaled by the a posteriori variance factor. Note some TG locations have been shifted horizontally by small amounts for clarity.

Table S4 summaries our estimates of VLM, RSL and ASL rates at the TG locations, in comparison with VLM trends from the GPS-Krig and GIA approaches. Also, the VLM trends at GPS locations from our approach are compared with the Hector-based estimates and GIA predictions in Table S5.

Table S4 Our a posteriori VLMs at TG locations versus GPS-Krig and ICE6G_D GIA trends, along with the RSL and our ASL estimates. Note the timespan of records and ± 1 -sigma uncertainties.

TG name	Lat (deg)	Lon (deg)	Time span	GPS-Krig VLM (mm/year)	GIA VLM (mm/year)	Our VLM (mm/year)	RSL estimates (mm/year)	Our ASL (mm/year)
BOOBY_ISL(BOOB)	-10.6	141.92	1992.7 2019.8	$+1.07 \pm 1.94$	-0.06 ± 1.0	-1.32 ± 1.02	$+6.09 \pm 1.03$	$+4.77 \pm 1.45$
BRISBANE(BRIS)	-27.37	153.17	1992.8 2020.1	-0.74 ± 0.94	-0.14 ± 1.0	-1.19 ± 0.82	$+3.99 \pm 0.37$	$+2.80 \pm 0.90$
BROOME(BROO)	-18.0	122.22	1992.8 2020.1	-0.81 ± 0.7	-0.22 ± 1.0	-0.2 ± 0.76	$+4.15 \pm 0.56$	$+3.94 \pm 0.94$
BUNDABERG(BUND)	-24.83	152.35	1992.7 2019.0	-0.37 ± 0.8	-0.13 ± 1.0	-1.45 ± 0.9	$+5.33 \pm 0.38$	$+3.88 \pm 0.98$
BURNIE(BURN)	-41.05	145.92	1992.7 2020.1	-1.17 ± 0.8	-0.21 ± 1.0	-0.4 ± 0.61	$+3.16 \pm 0.27$	$+2.76 \pm 0.67$
CAPE_FERGUSON(CAPE)	-19.28	147.06	1992.7 2020.1	-0.98 ± 0.78	-0.11 ± 1.0	-1.54 ± 0.74	$+5.55 \pm 0.32$	$+4.01 \pm 0.8$
CARNARVON(CARN)	-24.88	113.62	1992.7 2020.1	-0.27 ± 0.79	-0.27 ± 1.0	-0.66 ± 0.57	$+4.45 \pm 0.64$	$+3.79 \pm 0.86$
DARWIN(DARW)	-12.47	130.85	1992.7 2020.0	-0.34 ± 0.69	-0.07 ± 1.0	-0.77 ± 0.7	$+5.28 \pm 0.6$	$+4.51 \pm 0.92$
ESPERANCE(ESPE)	-33.87	121.9	1992.7 2020.0	-0.26 ± 0.49	-0.34 ± 1.0	-0.67 ± 0.47	$+3.85 \pm 0.43$	$+3.18 \pm 0.64$
FORT_DENISON(FORT)	-33.85	151.23	1992.7 2020.0	-0.38 ± 0.78	-0.2 ± 1.0	$+0.04 \pm 0.77$	$+3.43 \pm 0.3$	$+3.47 \pm 0.83$
FREMANTLE(FREM)	-32.05	115.73	1992.7 2020.1	-1.33 ± 0.73	-0.27 ± 1.0	-0.96 ± 0.53	$+4.38 \pm 0.56$	$+3.42 \pm 0.77$
HEDLAND(HEDL)	-20.32	118.57	1992.7 2019.2	-0.24 ± 0.79	-0.24 ± 1.0	$+0.4 \pm 0.82$	$+4.05 \pm 0.60$	$+4.45 \pm 1.02$
HILLARYS(HILL)	-31.83	115.74	1992.7 2020.1	-1.33 ± 0.72	-0.26 ± 1.0	-2.38 ± 0.52	$+5.82 \pm 0.58$	$+3.44 \pm 0.78$
KEMBLA(KEMB)	-34.47	150.91	1992.7 2020.1	-0.4 ± 0.81	-0.2 ± 1.0	-0.64 ± 0.68	$+3.84 \pm 0.28$	$+3.2 \pm 0.73$
LORNE(LORN)	-38.55	143.99	1993.0 2020.1	-0.49 ± 0.94	-0.25 ± 1.0	$+0.95 \pm 0.71$	$+2.01 \pm 0.35$	$+2.96 \pm 0.79$
MILNER_BAY(MILN)	-13.86	136.42	1993.7 2020.0	-0.14 ± 0.79	-0.14 ± 1.0	-0.85 ± 0.76	$+4.90 \pm 0.84$	$+4.05 \pm 1.13$
PORTLAND(PORT)	-38.34	141.61	1992.7 2020.1	-0.78 ± 0.92	-0.33 ± 1.0	$+0.49 \pm 0.6$	$+2.81 \pm 0.33$	$+3.30 \pm 0.68$
ROSSLYN_BAY(ROSS)	-23.16	150.79	1993.2 2020.1	-0.63 ± 1.17	-0.07 ± 1.0	-1.34 ± 0.84	$+4.59 \pm 0.3$	$+3.25 \pm 0.9$
SPRING_BAY(SPRI)	-42.55	147.93	1992.7 2020.0	-0.88 ± 0.66	-0.19 ± 1.0	-0.5 ± 0.56	$+3.39 \pm 0.23$	$+2.89 \pm 0.6$
STANVAC(STAN)	-35.11	138.47	1992.7 2009.1	-0.25 ± 1.07	-0.25 ± 1.0	-0.52 ± 0.71	$+5.15 \pm 0.81$	$+4.63 \pm 1.08$
STONY_POINT(STON)	-38.37	145.22	1993.0 2010.8	-0.8 ± 1.01	-0.19 ± 1.0	-0.15 ± 0.7	$+2.92 \pm 0.42$	$+2.77 \pm 0.82$
THEVENARD(THEV)	-32.15	133.64	1992.7 2019.4	-0.39 ± 0.7	-0.28 ± 1.0	$+0.54 \pm 0.64$	$+3.65 \pm 0.44$	$+4.19 \pm 0.78$
TOWNSVILLE(TOWN)	-19.25	146.83	1992.7 2016.7	-0.98 ± 0.78	-0.1 ± 1.0	-1.75 ± 0.88	$+4.65 \pm 0.56$	$+2.90 \pm 1.04$

Table S5 Our a posteriori VLMs at GPS sites against the Hector-derived and ICE6G_D GIA trends.
Note the timespan of observational records. All uncertainties are given at ± 1 -sigma level.

GPS name	Lat (de)	Lon (deg)	Time Span	Hector VLM (mm/year)	GIA VLM (mm/year)	Our VLM (mm/year)	GPS name	Lat (deg)	Lon (deg)	Time span	Hector VLM (mm/year)	GIA VLM (mm/year)	Our VLM (mm/year)
00NA	-12.47	130.84	2008.2 2018.7	-1.7 $\pm$ 0.59	-0.07 $\pm$ 1.0	-1.52 $\pm$ 0.53	CBTN	-34.06	150.82	2012.2 2019.7	-1.77 $\pm$ 0.97	-0.16 $\pm$ 1.0	-1.54 $\pm$ 0.58
4CDA	-28.24	153.56	2012.2 2015.9	+1.86 $\pm$ 1.38	-0.19 $\pm$ 1.0	+2.1 $\pm$ 1.52	CEDU	-31.87	133.81	1994.4 2019.7	-0.45 $\pm$ 0.34	-0.22 $\pm$ 1.0	-0.39 $\pm$ 0.48
A770	-24.16	151.89	2014.0 2019.7	+1.68 $\pm$ 0.51	-0.12 $\pm$ 1.0	+1.73 $\pm$ 0.62	CLEV	-27.53	153.27	2009.2 2019.7	-0.7 $\pm$ 0.67	-0.15 $\pm$ 1.0	-0.64 $\pm$ 0.5
ACA4	-27.6	153.04	2012.8 2018.9	+0.24 $\pm$ 1.0	-0.11 $\pm$ 1.0	+0.31 $\pm$ 0.67	CNLP	-35.69	139.85	2010.7 2019.6	-0.56 $\pm$ 0.69	-0.17 $\pm$ 1.0	-0.4 $\pm$ 0.52
ACL2	-27.27	151.7	2010.7 2019.6	-1.92 $\pm$ 0.79	+0.02 $\pm$ 1.0	-1.69 $\pm$ 0.51	COEN	-13.96	143.18	2013.5 2019.7	0.12 $\pm$ 1.1	-0.0 $\pm$ 1.0	+0.28 $\pm$ 0.78
ADE1	-34.73	138.65	1999.2 2011.5	-0.89 $\pm$ 0.5	-0.2 $\pm$ 1.0	-1.04 $\pm$ 0.41	COOR	-25.01	149.5	2013.6 2019.2	-0.66 $\pm$ 0.76	+0.01 $\pm$ 1.0	-0.49 $\pm$ 0.75
ADE2	-34.73	138.65	2005.8 2011.5	-1.5 $\pm$ 1.04	-0.2 $\pm$ 1.0	-1.74 $\pm$ 0.78	CRCW	-25.29	150.27	2013.6 2019.7	-0.66 $\pm$ 0.6	+0.02 $\pm$ 1.0	-0.61 $\pm$ 0.72
AMB1	-41.2	146.38	2013.6 2019.6	-1.68 $\pm$ 0.67	-0.18 $\pm$ 1.0	-1.59 $\pm$ 0.63	CRK1	-33.92	151.18	2010.7 2015.5	0.4 $\pm$ 0.81	-0.2 $\pm$ 1.0	+0.21 $\pm$ 0.9
ARRT	-37.28	142.93	2013.4 2019.6	-0.68 $\pm$ 1.03	-0.09 $\pm$ 1.0	-0.48 $\pm$ 0.62	CRKB	-27.44	153.05	2010.7 2019.7	-2.82 $\pm$ 0.85	-0.12 $\pm$ 1.0	-2.65 $\pm$ 0.53
BALA	-32.46	123.87	2012.0 2019.7	-0.34 $\pm$ 0.92	-0.21 $\pm$ 1.0	-0.41 $\pm$ 0.57	CRKP	-31.94	115.84	2010.7 2018.1	-1.2 $\pm$ 1.17	-0.25 $\pm$ 1.0	-1.04 $\pm$ 0.58
BALL	-37.56	143.85	2011.0 2019.6	-0.1 $\pm$ 0.72	-0.1 $\pm$ 1.0	-0.1 $\pm$ 0.51	CRL0	-27.54	153.42	2010.7 2019.7	-2.7 $\pm$ 0.82	-0.18 $\pm$ 1.0	-2.53 $\pm$ 0.56
BALM	-37.25	141.84	2013.4 2019.6	-0.83 $\pm$ 0.74	-0.14 $\pm$ 1.0	-0.62 $\pm$ 0.59	CRY4	-26.42	152.91	2012.0 2018.9	-1.48 $\pm$ 1.15	-0.13 $\pm$ 1.0	-1.6 $\pm$ 0.65
BANK	-33.92	151.04	2014.1 2019.6	-0.18 $\pm$ 0.93	-0.18 $\pm$ 1.0	-0.13 $\pm$ 0.71	CUAA	-32.0	115.89	2012.8 2019.7	-1.18 $\pm$ 0.91	-0.24 $\pm$ 1.0	-1.31 $\pm$ 0.6
BAT2	-33.43	149.57	2010.9 2019.6	-0.24 $\pm$ 0.72	-0.03 $\pm$ 1.0	-0.17 $\pm$ 0.55	CUAI	-32.0	115.89	2012.8 2019.7	-1.12 $\pm$ 0.87	-0.24 $\pm$ 1.0	-1.11 $\pm$ 0.6
BBOO	-32.81	136.06	2009.6 2019.7	-0.46 $\pm$ 0.62	-0.16 $\pm$ 1.0	-0.36 $\pm$ 0.49	CUBB	-32.0	115.89	2012.7 2019.7	-1.24 $\pm$ 0.94	-0.24 $\pm$ 1.0	-1.14 $\pm$ 0.61
BCMT	-28.13	153.19	2010.7 2019.0	+0.72 $\pm$ 0.86	-0.13 $\pm$ 1.0	+0.68 $\pm$ 0.54	CUC2	-32.0	115.89	2015.2 2019.7	-2.04 $\pm$ 1.32	-0.24 $\pm$ 1.0	-2.12 $\pm$ 0.93
BDLE	-37.76	147.66	2009.7 2019.7	-0.78 $\pm$ 0.66	-0.13 $\pm$ 1.0	-1.0 $\pm$ 0.51	CUT0	-32.0	115.89	2010.6 2019.7	-1.66 $\pm$ 0.57	-0.24 $\pm$ 1.0	-1.81 $\pm$ 0.51
BDRM	-26.68	153.07	2010.7 2019.0	-0.26 $\pm$ 0.84	-0.14 $\pm$ 1.0	-0.18 $\pm$ 0.54	CUT1	-32.0	115.89	2010.5 2019.0	-2.03 $\pm$ 0.69	-0.24 $\pm$ 1.0	-2.18 $\pm$ 0.54
BDST	-27.99	153.0	2009.2 2019.7	-0.8 $\pm$ 0.43	-0.1 $\pm$ 1.0	-0.89 $\pm$ 0.51	CUT3	-32.0	115.89	2012.4 2019.7	-1.52 $\pm$ 0.81	-0.24 $\pm$ 1.0	-1.59 $\pm$ 0.63
BER5	-34.28	140.6	2014.5 2019.7	-0.2 $\pm$ 0.84	-0.08 $\pm$ 1.0	-0.28 $\pm$ 0.71	DALB	-27.17	151.26	2010.6 2019.7	-2.6 $\pm$ 0.49	+0.03 $\pm$ 1.0	-2.66 $\pm$ 0.52
BIN2	-32.41	151.65	2012.0 2015.8	+1.74 $\pm$ 1.08	-0.12 $\pm$ 1.0	+1.89 $\pm$ 1.16	DARM	-12.42	130.89	2007.0 2014.8	-1.1 $\pm$ 0.51	-0.07 $\pm$ 1.0	-1.14 $\pm$ 0.56
BLMT	-31.95	115.93	2014.0 2019.7	-0.76 $\pm$ 0.5	-0.23 $\pm$ 1.0	-0.68 $\pm$ 0.72	DARR	-12.84	131.13	2002.5 2008.1	+1.81 $\pm$ 1.52	-0.02 $\pm$ 1.0	+1.92 $\pm$ 0.72
BNDY	-24.91	152.32	2007.7 2019.7	-0.66 $\pm$ 0.39	-0.12 $\pm$ 1.0	-0.78 $\pm$ 0.47	DARW	-12.84	131.13	1994.7 2019.7	-0.75 $\pm$ 0.41	-0.02 $\pm$ 1.0	-0.7 $\pm$ 0.48
BNLA	-36.54	146.01	2014.0 2019.6	-1.49 $\pm$ 1.38	-0.0 $\pm$ 1.0	-1.54 $\pm$ 0.67	DIXL	-23.94	150.27	2013.3 2017.8	-2.2 $\pm$ 0.81	-0.01 $\pm$ 1.0	-2.39 $\pm$ 0.59
BOLC	-37.71	142.84	2013.4 2019.6	-1.50 $\pm$ 0.96	-0.15 $\pm$ 1.0	-1.27 $\pm$ 0.59	DODA	-13.83	131.19	2009.8 2019.7	+0.33 $\pm$ 0.46	+0.01 $\pm$ 1.0	+0.43 $\pm$ 0.5
BRO1	-18.0	122.21	2010.5 2019.7	-0.81 $\pm$ 0.58	-0.23 $\pm$ 1.0	-0.78 $\pm$ 0.52	DPRT	-41.18	146.35	2015.2 2019.7	-2.11 $\pm$ 0.95	-0.18 $\pm$ 1.0	-2.11 $\pm$ 0.82
BRTN	-42.74	147.24	2010.8 2017.2	-0.03 $\pm$ 1.03	-0.16 $\pm$ 1.0	+0.11 $\pm$ 0.65	DWNI	-12.44	130.96	2010.4 2019.7	+0.96 $\pm$ 0.74	-0.06 $\pm$ 1.0	+1.06 $\pm$ 0.54
BUR1	-41.05	145.91	1999.3 2007.4	-0.70 $\pm$ 1.01	-0.21 $\pm$ 1.0	-0.89 $\pm$ 0.56	DYST	-22.6	148.5	2013.3 2018.3	+0.96 $\pm$ 1.51	-0.0 $\pm$ 1.0	+1.3 $\pm$ 0.59
BUR2	-41.05	145.91	2008.6 2019.7	-0.68 $\pm$ 0.49	-0.21 $\pm$ 1.0	-0.67 $\pm$ 0.47	EDS1	-25.38	151.12	2014.6 2019.6	-1.22 $\pm$ 0.73	+0.01 $\pm$ 1.0	-1.12 $\pm$ 0.78
BURA	-30.53	117.17	2008.9 2019.6	-0.21 $\pm$ 0.51	-0.12 $\pm$ 1.0	-0.20 $\pm$ 0.50	ENSH	-23.48	148.52	2010.7 2019.7	-0.53 $\pm$ 0.78	-0.0 $\pm$ 1.0	-0.38 $\pm$ 0.53
BUSS	-33.65	115.35	2014.9 2019.7	-1.27 $\pm$ 0.67	-0.35 $\pm$ 1.0	-1.19 $\pm$ 0.73	ESPA	-33.87	121.89	2008.5 2019.7	-0.26 $\pm$ 0.41	-0.34 $\pm$ 1.0	-0.42 $\pm$ 0.47
CAN3	-20.29	148.67	2013.0 2019.7	-0.48 $\pm$ 0.89	-0.12 $\pm$ 1.0	-0.32 $\pm$ 0.74	EXMT	-21.96	114.11	2012.7 2019.7	-0.11 $\pm$ 0.87	-0.32 $\pm$ 1.0	-0.12 $\pm$ 0.58
CBLT	-27.08	152.95	2007.1 2019.7	-0.83 $\pm$ 0.61	-0.11 $\pm$ 1.0	-0.91 $\pm$ 0.49	FLND	-40.21	148.24	2012.9 2019.7	-1.04 $\pm$ 1.2	-0.31 $\pm$ 1.0	-1.14 $\pm$ 0.68
CBRK	-33.35	138.21	2010.7 2017.3	-0.54 $\pm$ 1.06	-0.14 $\pm$ 1.0	-0.68 $\pm$ 0.64	FROY	-18.13	125.8	2012.7 2019.7	+0.69 $\pm$ 0.78	-0.03 $\pm$ 1.0	+0.83 $\pm$ 0.59

Table S5 Continued.

GPS name	Lat (de)	Lon (deg)	Time Span	Hector VLM (mm/year)	GIA VLM (mm/year)	Our VLM (mm/year)	GPS name	Lat (deg)	Lon (deg)	Time span	Hector VLM (mm/year)	GIA VLM (mm/year)	Our VLM (mm/year)
FTDN	-33.86	151.23	2012.5 2019.7	-0.53 ± 0.74	-0.2 ± 1.0	-0.61 ± 0.59	LAUN	-41.43	147.15	2010.7 2019.7	-0.4 ± 0.63	-0.16 ± 1.0	-0.27 ± 0.52
GASC	-24.63	115.34	2013.8 2019.7	-0.61 ± 0.92	-0.07 ± 1.0	-0.55 ± 0.74	LDHI	-31.54	159.08	2010.0 2019.2	-1.08 ± 0.56	-0.37 ± 1.0	-1.16 ± 0.53
GATT	-27.54	152.33	2008.2 2019.5	-0.21 ± 1.04	-0.03 ± 1.0	-0.16 ± 0.53	LEAR	-22.22	114.1	2011.7 2019.7	+0.26 ± 0.93	-0.29 ± 1.0	+0.32 ± 0.53
GERO	-28.78	114.61	2015.2 2019.7	-2.05 ± 0.78	-0.33 ± 1.0	-1.98 ± 0.83	LIAW	-41.9	146.67	2008.8 2019.7	-0.69 ± 0.49	-0.12 ± 1.0	-0.66 ± 0.46
GLAD	-23.84	151.25	2010.7 2019.7	-0.22 ± 0.85	-0.08 ± 1.0	-0.11 ± 0.55	LILY	-41.25	147.21	2015.2 2019.7	-0.48 ± 1.46	-0.18 ± 1.0	-0.36 ± 0.88
GLNC	-42.83	147.27	2015.6 2019.7	-2.65 ± 1.28	-0.17 ± 1.0	-2.6 ± 1.2	LKYA	-12.46	130.82	2011.6 2019.7	+0.57 ± 0.4	-0.07 ± 1.0	+0.46 ± 0.53
GOOM	-31.4	116.85	2014.2 2019.6	+0.29 ± 0.77	-0.13 ± 1.0	+0.24 ± 0.72	LORD	-31.52	159.06	2009.5 2019.7	-1.27 ± 0.52	-0.37 ± 1.0	-1.3 ± 0.51
GRN1	-33.86	116.06	2015.0 2019.7	-1.37 ± 0.76	-0.26 ± 1.0	-1.3 ± 0.83	LUC2	-37.04	140.27	2013.6 2017.1	-0.47 ± 1.03	-0.25 ± 1.0	-0.45 ± 1.18
GYM2	-26.19	152.66	2011.0 2018.0	-0.89 ± 1.08	-0.1 ± 1.0	-0.8 ± 0.59	MAIN	-14.05	134.09	2012.2 2019.7	2.04 ± 0.66	+0.05 ± 1.0	+2.14 ± 0.57
HBAY	-25.28	152.83	2010.7 2019.7	-0.22 ± 0.94	-0.16 ± 1.0	-0.13 ± 0.54	MAIT	-34.37	137.67	2010.7 2017.8	-0.18 ± 0.94	-0.24 ± 1.0	-0.27 ± 0.62
HBG2	-34.14	150.94	2013.9 2019.7	-0.32 ± 1.02	-0.18 ± 1.0	-0.28 ± 0.67	MANY	-35.05	141.06	2013.4 2018.9	-2.16 ± 0.99	-0.07 ± 1.0	-2.08 ± 0.68
HIL1	-31.83	115.74	1997.7 2019.7	-2.28 ± 0.32	-0.26 ± 1.0	-2.17 ± 0.55	MARY	-37.01	143.76	2013.4 2019.6	-0.97 ± 0.72	-0.05 ± 1.0	-0.83 ± 0.59
HNIS	-10.59	142.3	2010.7 2019.5	+1.72 ± 1.04	-0.05 ± 1.0	+1.84 ± 0.57	MBH4	-25.53	152.71	2012.8 2018.9	-1.27 ± 1.01	-0.13 ± 1.0	-1.14 ± 0.59
HNSB	-33.70	151.1	2012.8 2019.7	-0.83 ± 1.62	-0.17 ± 1.0	-0.71 ± 0.57	MCKN	-35.52	138.65	2014.1 2018.6	-0.89 ± 0.88	-0.28 ± 1.0	-0.98 ± 0.79
HOB2	-42.80	147.44	1994.5 2019.7	-0.97 ± 0.30	-0.18 ± 1.0	-1.04 ± 0.48	MCLV	-35.22	138.54	2010.7 2015.3	2.38 ± 0.81	-0.25 ± 1.0	+2.53 ± 0.96
HRSM	-36.72	142.17	2013.4 2019.6	-1.14 ± 0.73	-0.07 ± 1.0	-1.05 ± 0.61	MEDO	-26.76	114.61	2013.5 2019.7	+0.39 ± 1.1	-0.2 ± 1.0	+0.55 ± 0.64
INSF	-17.53	146.03	2013.7 2018.8	-0.05 ± 1.25	-0.12 ± 1.0	0.07 ± 0.84	MIDG	-20.64	148.71	2011.7 2019.7	+0.43 ± 0.83	-0.08 ± 1.0	+0.56 ± 0.57
IPS2	-27.61	152.76	2010.0 2014.2	-2.49 ± 1.21	-0.07 ± 1.0	-2.62 ± 1.05	MNDH	-32.53	115.71	2013.7 2017.8	-0.62 ± 0.9	-0.22 ± 1.0	-0.49 ± 1.01
IPSR	-27.61	152.76	2014.7 2019.7	-0.69 ± 0.70	-0.07 ± 1.0	-0.62 ± 0.73	MNGO	-38.78	143.65	2012.1 2019.7	-0.57 ± 1.24	-0.3 ± 1.0	-0.67 ± 0.59
JAB2	-12.66	132.89	2008.7 2019.7	+0.81 ± 0.55	+0.05 ± 1.0	+0.67 ± 0.5	MNTO	-24.87	151.13	2014.3 2019.7	+1.02 ± 1.02	-0.01 ± 1.0	+1.22 ± 0.72
JOON	-31.73	115.75	2013.6 2019.7	+0.48 ± 0.83	-0.27 ± 1.0	+0.42 ± 0.63	MOBS	-37.83	144.98	2002.8 2019.7	-0.91 ± 0.38	-0.12 ± 1.0	-0.87 ± 0.34
KARO	-35.10	139.89	2010.7 2017.3	-0.39 ± 1.03	-0.13 ± 1.0	-0.49 ± 0.62	MOOR	-37.40	142.13	2013.4 2019.6	-1.3 ± 0.99	-0.14 ± 1.0	-1.17 ± 0.65
KARR	-20.98	117.1	1994.8 2019.7	-0.74 ± 0.32	-0.19 ± 1.0	-0.71 ± 0.48	MRNO	-37.72	141.55	2013.4 2019.6	-0.51 ± 0.84	-0.22 ± 1.0	-0.3 ± 0.62
KAT1	-14.38	132.15	2010.2 2019.7	0.45 ± 0.58	+0.04 ± 1.0	+0.51 ± 0.51	MRNT	-38.23	145.07	2014.0 2019.6	-1.43 ± 1.42	-0.17 ± 1.0	-1.34 ± 0.67
KAT2	-14.38	132.15	2010.2 2019.7	-0.08 ± 0.42	+0.04 ± 1.0	+0.03 ± 0.52	MRO1	-26.7	116.64	2013.8 2019.7	-0.19 ± 0.74	-0.1 ± 1.0	-0.06 ± 0.64
KDNA	-33.97	137.72	2012.1 2015.9	+0.34 ± 0.81	-0.2 ± 1.0	0.34 ± 1.35	MRT1	-19.76	146.83	2014.9 2019.6	-1.82 ± 1.01	-0.06 ± 1.0	-1.90 ± 0.87
KELN	-31.62	117.7	2009.1 2019.6	-0.97 ± 0.41	-0.08 ± 1.0	-0.96 ± 0.47	MRT2	-19.46	147.48	2014.9 2019.6	-1.8 ± 0.61	-0.13 ± 1.0	-1.69 ± 0.78
KGIS	-39.94	143.85	2013.9 2019.7	-1.67 ± 1.10	-0.41 ± 1.0	-1.72 ± 0.66	MRT3	-19.33	146.52	2014.9 2019.6	+0.95 ± 1.06	-0.07 ± 1.0	+1.00 ± 1.00
KILK	-26.08	152.25	2013.5 2019.7	-0.16 ± 0.73	-0.05 ± 1.0	-0.15 ± 0.64	MRYB	-35.15	139.26	2010.7 2019.6	+0.69 ± 0.87	-0.18 ± 1.0	+0.87 ± 0.51
KIN2	-26.54	151.84	2013.6 2019.7	+0.30 ± 0.79	-0.0 ± 1.0	+0.16 ± 0.66	MTB2	-35.06	138.86	2015.0 2019.7	-0.27 ± 0.69	-0.21 ± 1.0	-0.16 ± 0.76
KJNG	-33.51	150.79	2012.8 2019.7	+0.93 ± 0.90	-0.11 ± 1.0	+0.85 ± 0.63	MTEM	-37.59	143.45	2011.4 2019.7	+0.25 ± 0.8	-0.11 ± 1.0	+0.39 ± 0.53
KOUM	-21.61	149.24	2011.7 2019.7	-1.03 ± 0.96	-0.05 ± 1.0	-0.91 ± 0.59	MTGA	-37.83	140.78	2010.9 2019.7	-0.91 ± 0.58	-0.31 ± 1.0	-0.82 ± 0.5
KTHA	-20.73	116.84	2014.1 2019.7	+0.21 ± 0.92	-0.24 ± 1.0	+0.17 ± 0.67	MULG	-30.28	134.06	2014.7 2019.7	-0.76 ± 1.16	-0.11 ± 1.0	-0.69 ± 0.78
KURR	-32.80	151.49	2010.7 2019.5	-0.34 ± 0.98	-0.14 ± 1.0	-0.32 ± 0.59	MURM	-35.06	149.09	2010.9 2019.6	-1.01 ± 0.7	-0.04 ± 1.0	-0.98 ± 0.53
LAM1	-35.33	140.51	2010.7 2017.4	-1.13 ± 0.94	-0.1 ± 1.0	-1.25 ± 0.63	MYAP	-33.06	115.74	2015.8 2019.7	-0.72 ± 1.51	-0.18 ± 1.0	-0.59 ± 1.16
LARR	-15.57	133.21	2009.8 2019.7	-0.4 ± 0.45	+0.01 ± 1.0	-0.51 ± 0.49	NELN	-38.05	141.01	2013.4 2019.6	+0.09 ± 0.64	-0.32 ± 1.0	-0.0 ± 0.59

Table S5 Continued.

GPS name	Lat (de)	Lon (deg)	Time Span	Hector VLM (mm/year)	GIA VLM (mm/year)	Our VLM (mm/year)	GPS name	Lat (deg)	Lon (deg)	Time span	Hector VLM (mm/year)	GIA VLM (mm/year)	Our VLM (mm/year)
NEWE	-32.92	151.79	2012.5 2019.7	+0.08 ± 0.68	-0.19 ± 1.0	+0.14 ± 0.6	SYDN	-33.78	151.15	2004.4 2019.7	-0.45 ± 0.65	-0.18 ± 1.0	-0.45 ± 0.39
NHAV	-34.79	138.49	2012.1 2019.7	+1.6 ± 0.81	-0.22 ± 1.0	+1.71 ± 0.54	SYM1	-35.34	149.16	2014.7 2019.7	-0.77 ± 0.8	-0.05 ± 1.0	-0.52 ± 0.71
NHIL	-36.31	141.65	2010.6 2019.7	+1.48 ± 0.88	-0.07 ± 1.0	+1.4 ± 0.57	TER4	-23.96	148.78	2013.3 2019.7	-0.2 ± 0.58	-0.0 ± 1.0	+0.04 ± 0.59
NNOR	-31.05	116.19	2002.5 2019.7	-1.21 ± 0.65	-0.19 ± 1.0	-1.14 ± 0.33	THE1	-24.95	150.08	2013.4 2017.4	-1.25 ± 1.46	+0.01 ± 1.0	-1.0 ± 1.34
NORS	-32.26	121.79	2009.2 2019.7	-0.52 ± 0.61	-0.13 ± 1.0	-0.64 ± 0.49	THEV	-32.13	133.7	2013.2 2019.7	+0.7 ± 1.52	-0.27 ± 1.0	+0.52 ± 0.67
ORA2	-34.0	150.74	2012.8 2018.9	-1.57 ± 1.13	-0.14 ± 1.0	-1.6 ± 0.69	TID1	-35.4	148.98	1996.5 2019.7	-0.54 ± 0.65	-0.04 ± 1.0	-0.34 ± 0.48
PERT	-31.8	115.89	1992.4 2019.7	-2.81 ± 0.65	-0.24 ± 1.0	-3.02 ± 0.48	TID2	-35.4	148.98	1994.7 2010.5	-0.13 ± 0.65	-0.04 ± 1.0	-0.08 ± 0.31
PINN	-35.26	140.91	2012.1 2017.7	+0.99 ± 1.3	-0.08 ± 1.0	+0.93 ± 0.88	TIDB	-35.4	148.98	1994.6 2019.6	-0.8 ± 0.65	-0.04 ± 1.0	-0.65 ± 0.48
PNRY	-34.31	138.42	2012.1 2016.1	+0.73 ± 1.69	-0.18 ± 1.0	+0.82 ± 1.23	TITG	-10.59	142.22	2015.8 2019.7	-1.66 ± 0.81	-0.05 ± 1.0	-1.44 ± 1.29
POCA	-38.62	143.0	2013.4 2019.6	-0.42 ± 0.77	-0.3 ± 1.0	-0.26 ± 0.6	TNDA	-34.51	138.98	2010.7 2016.4	+0.48 ± 1.2	-0.16 ± 1.0	+0.67 ± 0.74
PRO1	-26.16	151.6	2011.1 2019.7	-1.6 ± 0.64	+0.01 ± 1.0	-1.65 ± 0.54	TNGL	-24.49	150.57	2013.4 2019.7	-1.01 ± 0.78	-0.0 ± 1.0	-0.86 ± 0.64
PRTF	-38.38	142.24	2013.4 2019.6	+0.12 ± 0.76	-0.29 ± 1.0	+0.25 ± 0.59	TOMP	-22.85	117.4	2013.0 2019.7	+1.38 ± 0.87	-0.04 ± 1.0	+1.57 ± 0.67
PTKL	-34.48	150.91	2009.7 2019.6	-0.53 ± 0.62	-0.2 ± 1.0	-0.39 ± 0.51	TOOG	-27.08	152.37	2014.5 2019.7	+0.07 ± 0.59	-0.04 ± 1.0	+0.23 ± 0.72
PTLD	-38.34	141.61	2009.7 2019.7	-0.66 ± 0.67	-0.33 ± 1.0	-0.61 ± 0.51	TOOW	-27.53	151.93	2009.8 2019.7	-0.56 ± 0.87	+0.01 ± 1.0	-0.55 ± 0.52
PTSV	-35.09	138.49	2010.7 2019.7	-0.81 ± 0.59	-0.24 ± 1.0	-0.67 ± 0.5	TOW2	-19.27	147.06	1995.0 2019.7	-0.8 ± 0.37	-0.11 ± 1.0	-0.85 ± 0.5
QCLF	-38.27	144.64	2013.4 2019.6	-1.76 ± 1.1	-0.19 ± 1.0	-1.9 ± 0.63	TRN1	-26.8	151.9	2011.6 2019.6	+0.64 ± 1.4	-0.0 ± 1.0	+0.86 ± 0.68
RAVN	-33.6	120.07	2010.3 2019.6	-0.36 ± 0.54	-0.21 ± 1.0	-0.30 ± 0.49	TURO	-36.04	150.12	2011.3 2019.7	-0.16 ± 0.62	-0.2 ± 1.0	-0.12 ± 0.55
RHPT	-41.07	145.96	2008.0 2019.7	-1.8 ± 0.4	-0.21 ± 1.0	-1.93 ± 0.47	TWED	-28.35	153.40	2010.7 2019.0	-2.59 ± 1.26	-0.16 ± 1.0	-2.67 ± 0.6
RID1	-23.29	150.21	2013.0 2019.7	-2.8 ± 0.98	-0.03 ± 1.0	-2.65 ± 0.62	UNX2	-33.92	151.23	2013.4 2017.6	-0.66 ± 1.44	-0.2 ± 1.0	-0.49 ± 1.26
ROBI	-28.08	153.38	2007.1 2019.7	-0.48 ± 0.52	-0.16 ± 1.0	-0.57 ± 0.49	UNX3	-33.92	151.23	2013.4 2017.6	-0.49 ± 1.44	-0.2 ± 1.0	-0.41 ± 1.3
ROC2	-23.38	150.51	2014.0 2018.3	-2.26 ± 1.15	-0.04 ± 1.0	-2.07 ± 1.12	WAGN	-33.33	117.41	2010.2 2019.7	-1.24 ± 0.58	-0.12 ± 1.0	-1.09 ± 0.49
ROS5	-24.63	151.91	2014.3 2019.7	-2.07 ± 0.58	-0.09 ± 1.0	-1.81 ± 0.68	WAIK	-34.2	140.0	2010.7 2016.4	-0.31 ± 1.14	-0.09 ± 1.0	-0.44 ± 0.71
RSBY	-23.16	150.79	2011.6 2019.7	+0.88 ± 0.62	-0.07 ± 1.0	+0.75 ± 0.63	WARW	-28.21	152.03	2010.7 2019.7	+0.5 ± 0.73	+0.0 ± 1.0	+0.3 ± 0.53
SG36	-37.91	145.13	2003.9 2010.8	-0.4 ± 0.86	-0.12 ± 1.0	-0.26 ± 0.59	WEDD	-36.43	143.61	2013.4 2019.6	-0.15 ± 0.88	-0.03 ± 1.0	-0.16 ± 0.6
SKIP	-37.68	143.36	2013.4 2019.6	+1.35 ± 0.63	-0.13 ± 1.0	+1.54 ± 0.6	WEND	-37.54	143.83	2015.5 2019.6	+0.0 ± 1.41	-0.1 ± 1.0	+0.24 ± 0.99
SPA7	-32.01	115.9	2014.2 2019.7	-1.93 ± 1.07	-0.24 ± 1.0	-2.26 ± 0.69	WIL3	-33.03	116.88	2010.7 2016.5	-0.31 ± 1.04	-0.13 ± 1.0	-0.48 ± 0.79
SPBY	-42.55	147.93	2008.8 2019.7	-1.02 ± 0.49	-0.19 ± 1.0	-1.1 ± 0.47	WLAL	-19.78	120.64	2011.9 2019.7	+0.43 ± 0.82	-0.23 ± 1.0	+0.63 ± 0.53
SSCK	-40.96	145.58	2012.1 2017.8	-1.72 ± 1.15	-0.24 ± 1.0	-1.55 ± 0.7	WNBL	-38.38	142.48	2013.9 2019.6	-1.16 ± 0.58	-0.28 ± 1.0	-1.12 ± 0.67
STA2	-36.62	143.26	2013.4 2017.3	-0.02 ± 1.38	-0.04 ± 1.0	+0.06 ± 1.01	WOOL	-27.48	153.04	2007.1 2018.4	-1.04 ± 0.7	-0.12 ± 1.0	-0.93 ± 0.5
STLW	-22.48	149.59	2013.6 2019.7	-0.52 ± 1.17	-0.03 ± 1.0	-0.3 ± 0.7	WOR1	-37.78	145.53	2014.0 2019.6	-2.08 ± 0.81	-0.1 ± 1.0	-1.85 ± 0.71
STNY	-38.38	145.21	2011.4 2019.7	-0.37 ± 0.85	-0.19 ± 1.0	-0.16 ± 0.53	YAR1	-29.05	115.35	1994.0 2002.4	-0.6 ± 1.05	-0.24 ± 1.0	-0.77 ± 0.53
STR1	-35.32	149.01	1998.5 2019.7	-0.75 ± 0.32	-0.04 ± 1.0	-0.68 ± 0.48	YAR2	-29.05	115.35	1996.5 2019.6	+0.41 ± 0.34	-0.24 ± 1.0	+0.56 ± 0.48
STR2	-35.32	149.01	2002.5 2019.7	-0.72 ± 0.48	-0.04 ± 1.0	-0.63 ± 0.35	YAR3	-29.05	115.35	2007.5 2019.6	-0.5 ± 0.41	-0.24 ± 1.0	-0.56 ± 0.46
STR4	-35.32	149.01	2010.7 2019.7	-0.75 ± 0.64	-0.04 ± 1.0	-0.99 ± 0.54	YNKI	-38.81	146.22	2013.4 2019.7	+0.21 ± 1.01	-0.23 ± 1.0	+0.19 ± 0.62
STRH	-37.73	141.14	2013.4 2019.6	-2.53 ± 0.92	-0.26 ± 1.0	-2.2 ± 0.75	YOR5	-35.02	137.61	2014.3 2018.9	+2.07 ± 0.81	-0.31 ± 1.0	+1.76 ± 1.03

S2.4 Sensitivity analysis

We undertook a suite of experiments to evaluate the improvements gained from multi-mission datasets against the reference-mission-only implementation, understanding the reliability of our estimates and the potential presence of geophysical and oceanographic signals in our estimates, and investigating the dependence of our estimates to the a priori configurations and assumptions.

S2.4.1 Impact of expanded altimeter dataset

We first compared the performance of the multi-mission and reference-mission solutions to provide the insight into the potential advantage of expanded altimeter datasets. We found significant differences in the VLM trends from the multi-mission and reference-mission solutions for the TGs situated at higher latitudes, as shown in Fig. S21. Compared to the GPS-Krig interpolations, the STD of the differences of TG VLM trends from multi-mission and reference-mission solutions were 0.74 and 0.83 mm/year, respectively. The multi-mission solution further resulted in a $\sim 35\%$ reduction in the formal errors of VLM rates. These highlight that our multi-mission estimates of time-fixed VLM at the TGs were more consistent to the Hector-inferred VLM rates at the nearby GPS sites. The multi-mission solution slightly better captured the nonlinear VLM stack at the TGs, with the STD of 1.46 mm versus 1.40 mm from the reference-mission solution, yielded with a $\sim 48\%$ increase in the respective correlation from +0.23 to +0.34 with the benchmark raw GPS stack (compare Figs. 5 and S22).

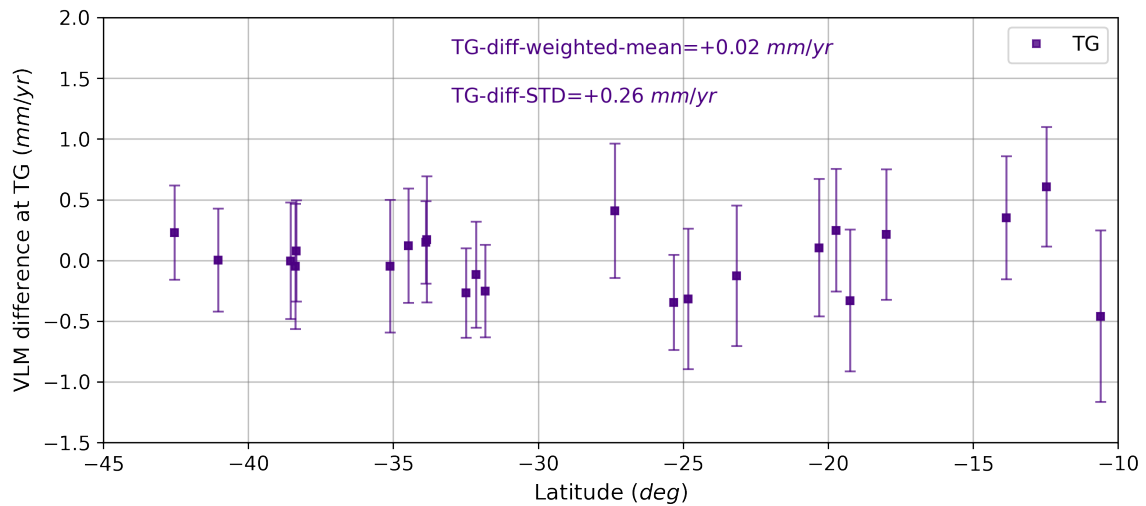


Fig. S21 Profile of VLM differences from the multi-mission and reference-mission solutions, as a function of latitude. The weighted average and standard deviation (STD) of the differences are annotated. Error bars are ± 1 -sigma scaled by the a posteriori variance factor. For clarity, TG latitudes at CAPE, CARN and FREM locations are shifted by -0.45 degrees.

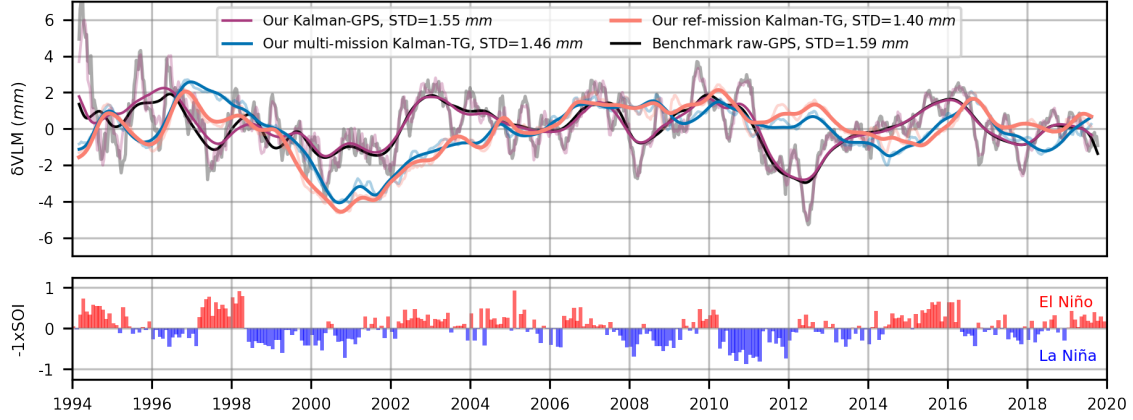


Fig. S22 Weighted average stack of our estimates of nonlinear VLMs at TGs from reference-mission (pink line) and multi-mission (blue line) solutions, and coastal GPS sites (purple line) around the Australian continent, with respect to the control stack derived from detrended GPS height series (black line). For comparison, Southern Oscillation Index (SOI) with the sign reversed is shown in the lower panel as the climatic descriptor in the region. The standard deviations (STDs) of the stacked series are annotated.

We inferred the same pattern of time-variable patterns for the Jason-series altimeter errors where the reference-mission-only datasets were used (Fig. S23). This further add our confidence to the derived pattern of time-variability in the first 3.5 years of the Jason-2 performance from the multi-mission datasets (compare Figs. 6 and S23).

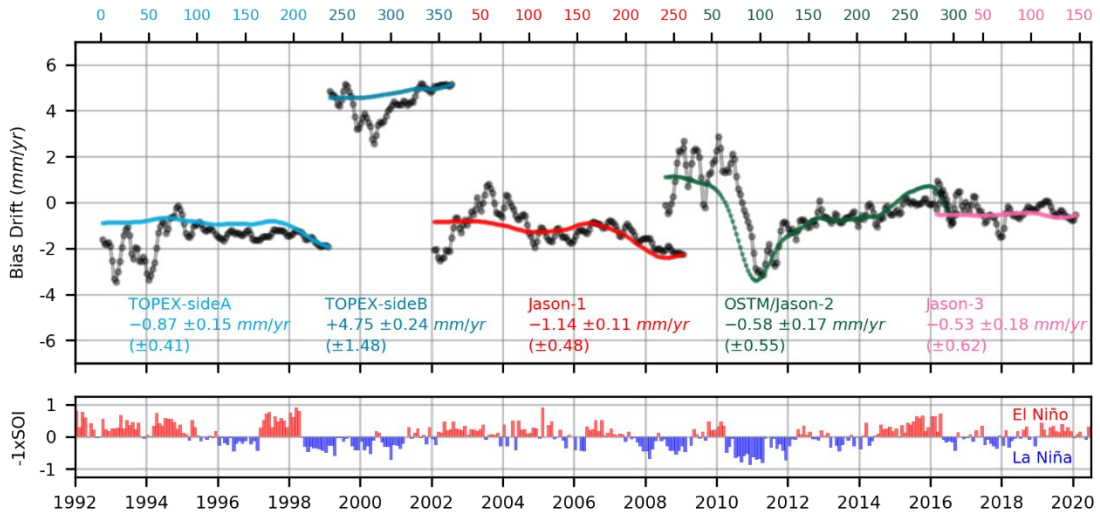


Fig. S23 Estimated time-dependent systematic errors of the reference altimeters around the study region from Solution 3, in a scenario when the reference-mission-only dataset was used. Comparing this with Fig. 6 reveals a similar pattern of time-variability for the Jason-2 bias drift. The smoothed averages of mission-specific systematic errors with the 1-sigma uncertainties are annotated, and the filter-based uncertainties are given in brackets. For comparison, the sign-inversed Southern Oscillation Index (SOI) is shown in the lower panel.

We thus noticed a slight improvement in the coherence of the resultant ASL trends at TG locations (Fig. S24), and a $\sim 13\%$ decrease in the geographical variability of the ASL trends (i.e., with the RMSE of 0.39 versus of 0.45 mm/year from fitting a quadratic polynomial to the resulted TG ASLs, see Fig. S25). The averaged ASL rise in the region was estimated to be $+3.41 \pm 0.38$ mm/year using the reference-mission data, approximately equivalent to the $+3.40 \pm 0.34$ mm/year from the multi-mission solution (note the latter has slightly smaller uncertainty).

Further investigations also suggest that the impact of differential oceanic signals could be partly mitigated given the multi-mission ground tracks generally get closer to the TG locations, with less noise amplitudes (see Figs. 9, 10 and 11).

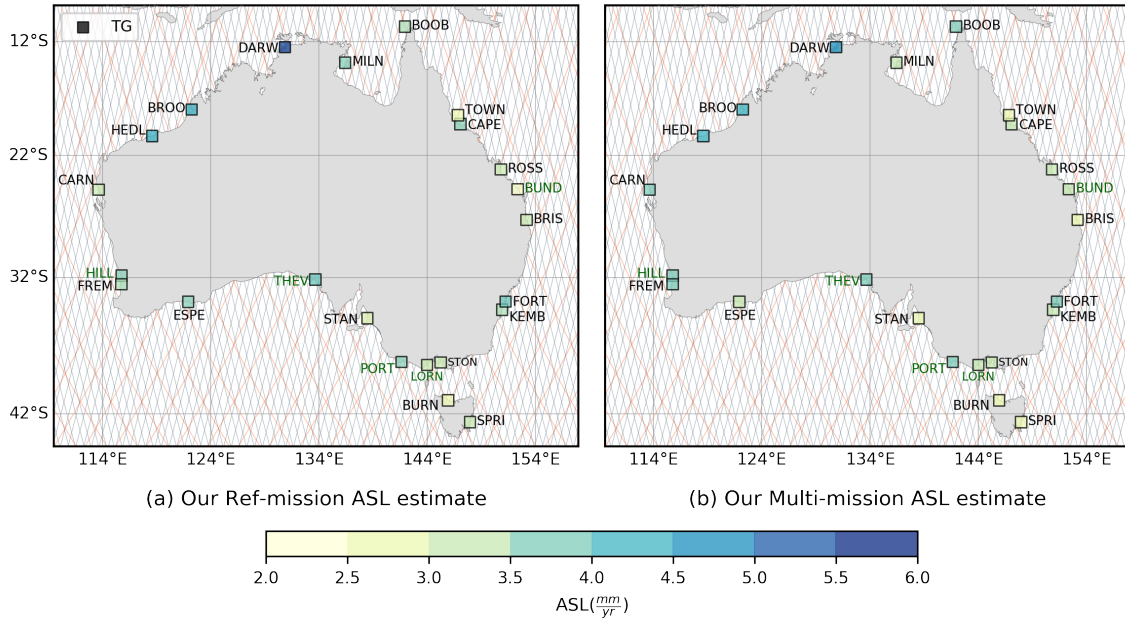


Fig. S24 Map of ASL at TG locations resulted by (a) reference-mission versus (b) multi-mission solutions. TGs with 1-sigma significant differences of our VLMs minus GPS-Krig are annotated in green in the left and right panels. For clarity, TG latitudes at TOWN and FREM locations are shifted by $+0.75$ and -0.45 degrees, respectively. The ground tracks of Jason-series and Envisat-series altimeters are shown in orange and grey, respectively.

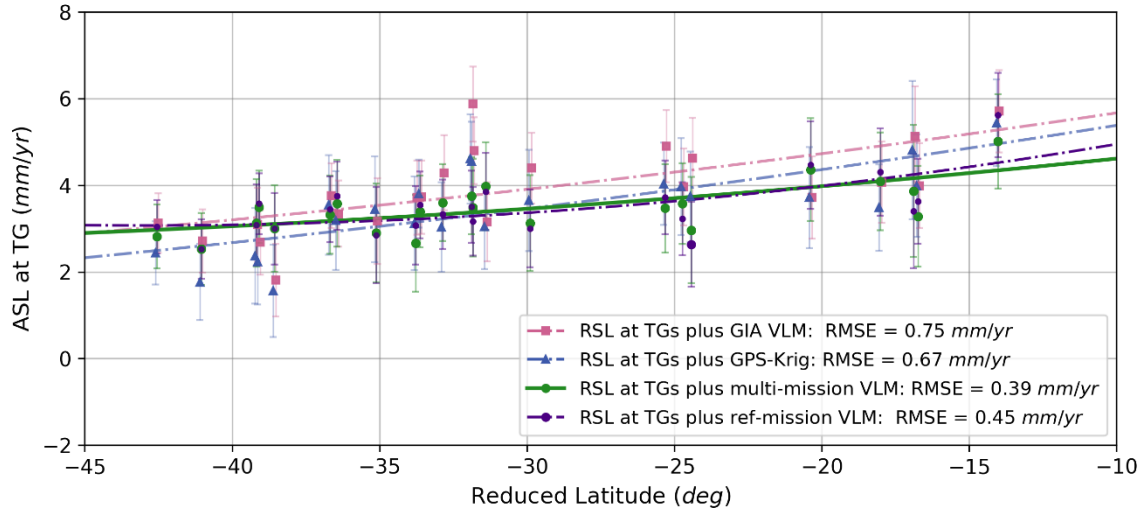


Fig. S25 Profile of ASL trends at TGs per latitude, comparing estimates derived using our ref-mission VLM (purple circles), with multi-mission VLM (green circles), GPS-Krig (blue triangles) and ICE6G_D GIA (pink squares) trends. Solid and dashed lines show a quadratic polynomial fitted to each set of ASL estimates per latitude reduced to the SE-NW direction, with root mean squared error (RMSE) about this fit annotated in the legend. For clarity, TG latitudes at STON and CARN locations are shifted by -0.75 degrees, and TG latitudes at PORT, ESPE, HILL, THEV and TOWN locations are shifted by $+0.75$ degrees. The latitudes of TGs where ASL is derived from GIA and GPS-Krig are also shifted by $+0.045$ and -0.045 degrees, respectively. Error bars are ± 1 -sigma scaled by the a posteriori variance factor.

S2.4.2 Impact of time-variable altimeter systematic errors

Second, we investigated the impact of estimating the nonlinearity in the bias drifts on the variability of nonlinear VLM stack at the TGs. To do so, we ran the multi-stage solution approach, while the altimeter systematic errors was treated as either time-fixed or time-variable quantities. The solution with the linear assumption of multi-mission bias drifts increased the STD of the weighted average stack of TG nonlinear VLMs, from 1.46 to 2.69 mm, per the preferred solution (compare Figs. 5 and S26). This supported the possibility of time-variable behaviour in the mission-specific bias drifts, especially in the first ~ 3.5 years of Jason-2 operation.

In the meantime, this experiment showed good consistency between the weighted average estimates of time-fixed and time-variable bias drifts across each mission (compare Fig. 6 with Fig. S27), with an average of -0.05 mm/year and STD of 0.25 mm/year of the differences. This internal agreement added further confidence to our interpretation regarding the likely presence of non-zero regionally-coherent systematic errors in the Australian altimetry datasets.

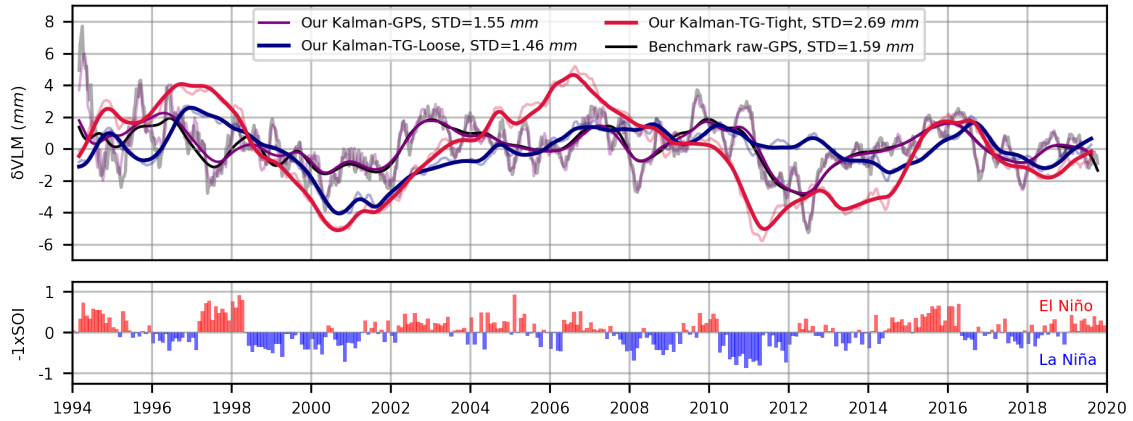


Fig. S26 Weighted average stack of our estimates of nonlinear VLMs at the TGs with time-fixed (red line) and time-variable (blue line) treatments of the bias drifts, and coastal GPS sites (purple line) around the Australian continent, with respect to the control stack derived from detrended GPS height series (black line). For comparison, Southern Oscillation Index (SOI) with the sign reversed is shown in the lower panel as the climatic descriptor in the region. The standard deviations (STDs) of the stacked series are annotated.

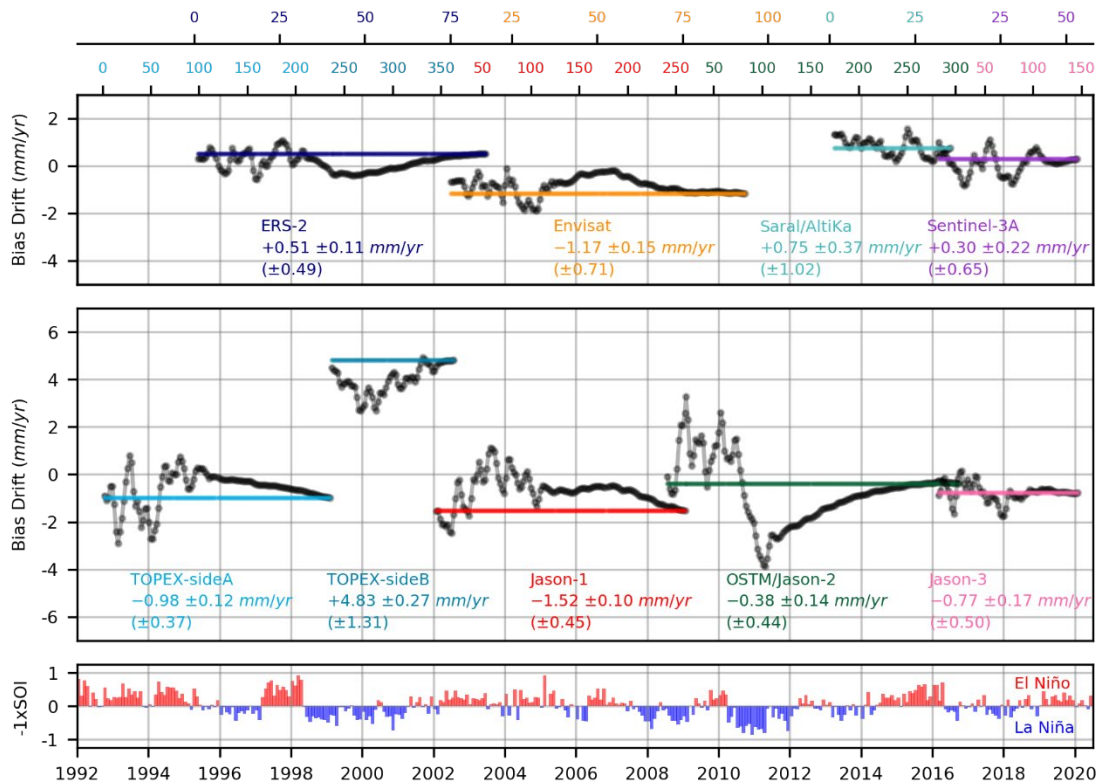


Fig. S27 Estimated time-fixed systematic errors of each altimeter mission over the study region, from the solution with bias drifts treated as time-fixed quantities. The smoothed averages of mission-specific bias drifts are annotated with the 1-sigma uncertainties, scaled by the a posteriori variance factor. The filtering uncertainties are given in brackets. The sign-inversed Southern Oscillation Index (SOI) is shown in the lower panel.

S2.4.3 Impact of nonlinear VLM estimates

Third, we evaluated the impact of estimating the nonlinear VLMs at the TGs on the time-variable pattern of the altimeter systematic errors. We ran the multi-stage solution approach with the nonlinear components of TG VLM constrained to be zero. This reveals small shifts in the resultant averages of altimeter-specific bias drifts (ranging from -0.73 mm/year for SARAL to $+0.89$ mm/year for TOPEX-side B), relative to the preferred solution. We further found a substantial change in the pattern of Jason-2 drift, with a clear exacerbation of the anomaly in the 2010-2012 period (compare Figs. 6 and S28). This experiment emphasizes the important role of accounting the nonlinear TG VLMs in appropriate capturing the time-variable bias drifts in our solutions.

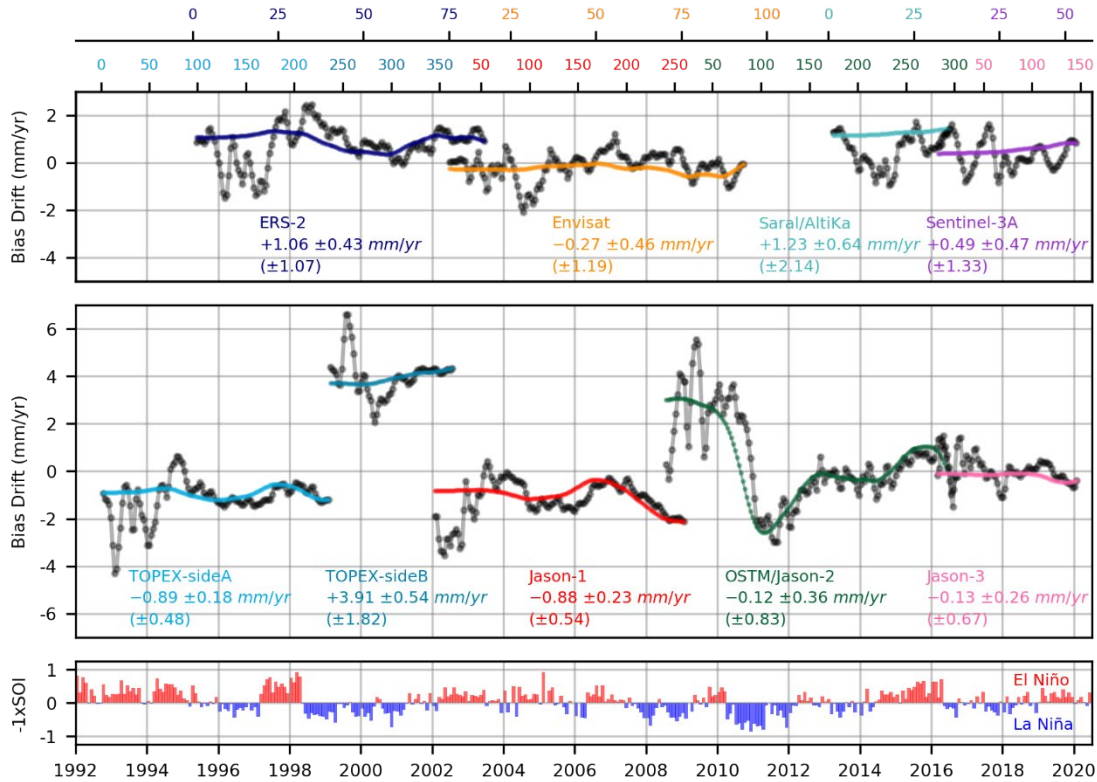
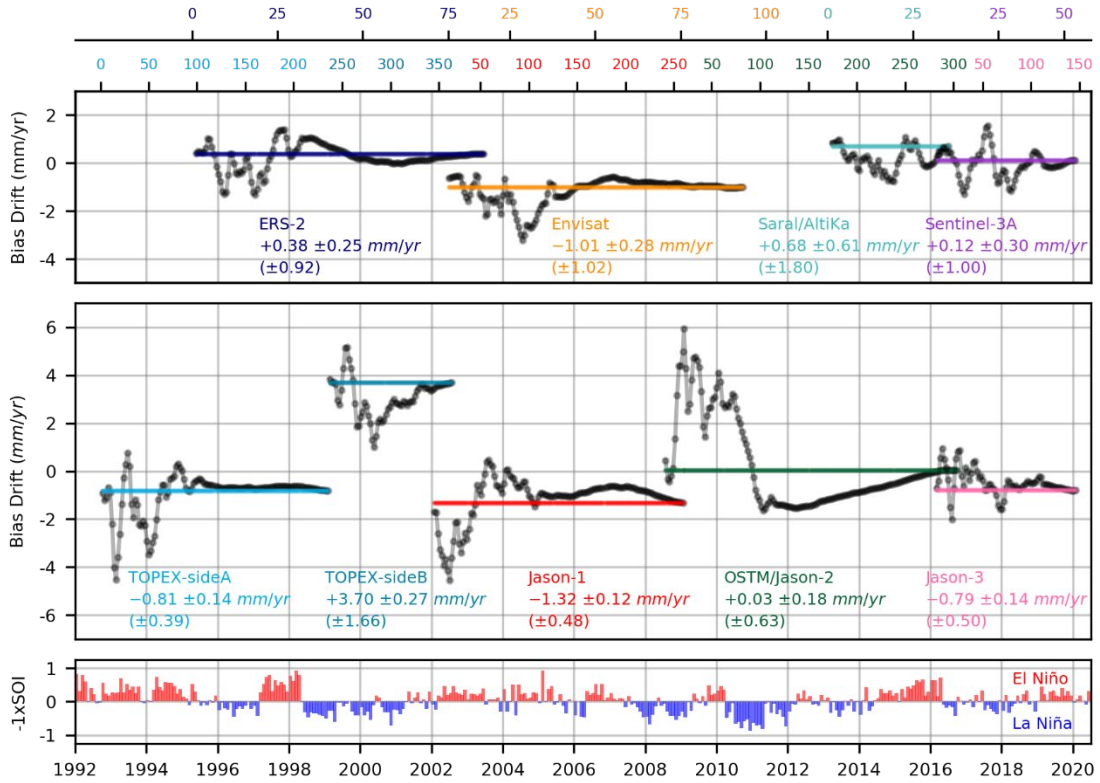


Fig. S28 Mission-specific bias drifts in a solution when the nonlinear VLMs constrained to be zero at all TG locations. Note an anomalous variability of Jason-2 bias drift, compared with Fig. 6. The smoothed averages of mission-specific bias drifts are annotated with the 1-sigma uncertainties, scaled by the a posteriori variance factor. The filtering uncertainties are given in brackets. The sign-inversed Southern Oscillation Index (SOI) is shown in the lower panel.

We further repeated this experiment, but the bias drifts assumed to behave linearly in time (Fig. S29). This yielded comparable results for the bias drifts with a weighted average discrepancy of

−0.12 mm/year and the STD of 0.43 mm/year, confirming the estimated magnitudes in the region were internally consistent (compare Figs. S28 and S29).



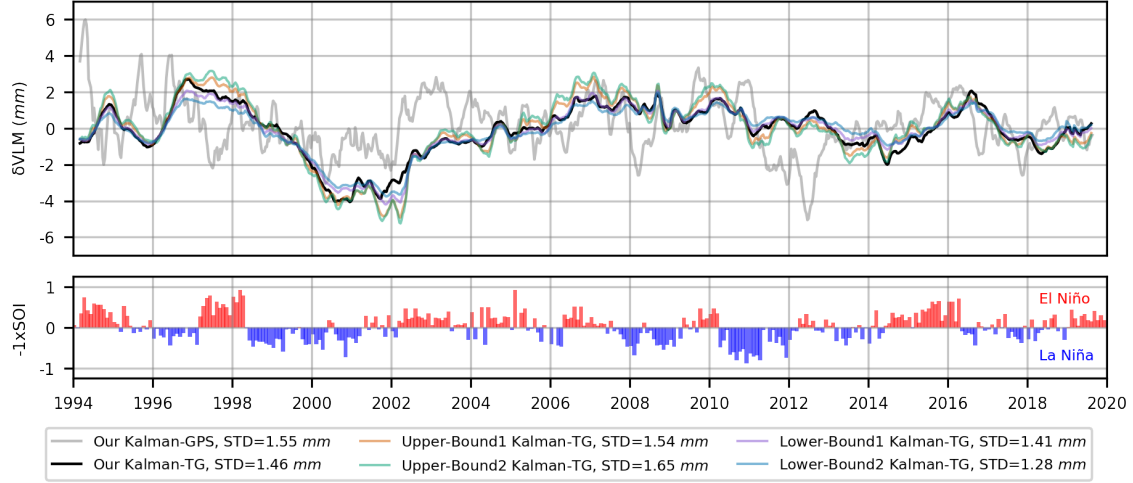


Fig. S30 Weighted average stack of nonlinear VLMs at TGs from our preferred solution (in black), against sensitivity solutions with upper and lower bounded changes in the respective process noise (in green, orange, purple and blue), and the stacked nonlinear VLMs at GPS sites (in grey). For comparison, Southern Oscillation Index (SOI) with the sign reversed is shown in the lower panel as the climatic descriptor in the region. The standard deviations (STDs) of the stacked series are annotated.

S2.4.4 Impact of climate-induced variability

Fourth, we investigated the potential presence of geophysical and oceanographic signals in our estimates of altimeter systematic errors, that were not utterly captured in the linear and nonlinear VLM estimates. We ran multi-stage solution approach with the Southern Oscillation Index (SOI) introduced as the covariate in the mathematical setup of the problem. This investigation reveals an approximately same pattern of time-variable bias drifts, supporting the results from our preferred solution were not severely be affected by the unmodelled signals across land and ocean (compare Figs. 6 and S31).

We found the correlations of -0.55 , -0.64 , -0.62 , -0.51 , -0.41 , -0.59 , -0.38 , -0.08 , and -0.45 between the SOI and the systematic errors of TOPEX-side A, TOPEX-side B, Jason-1, Jason-2, Jason-3, ERS-2, Envisat, SARAL and Sentinel-3A missions, respectively.

We inferred an approximately same pattern of time-variability in the estimates of nonlinear VLM stack at the TG and GPS sites, further supporting the results from our preferred solution (compare Fig. 5 with Fig. S32).

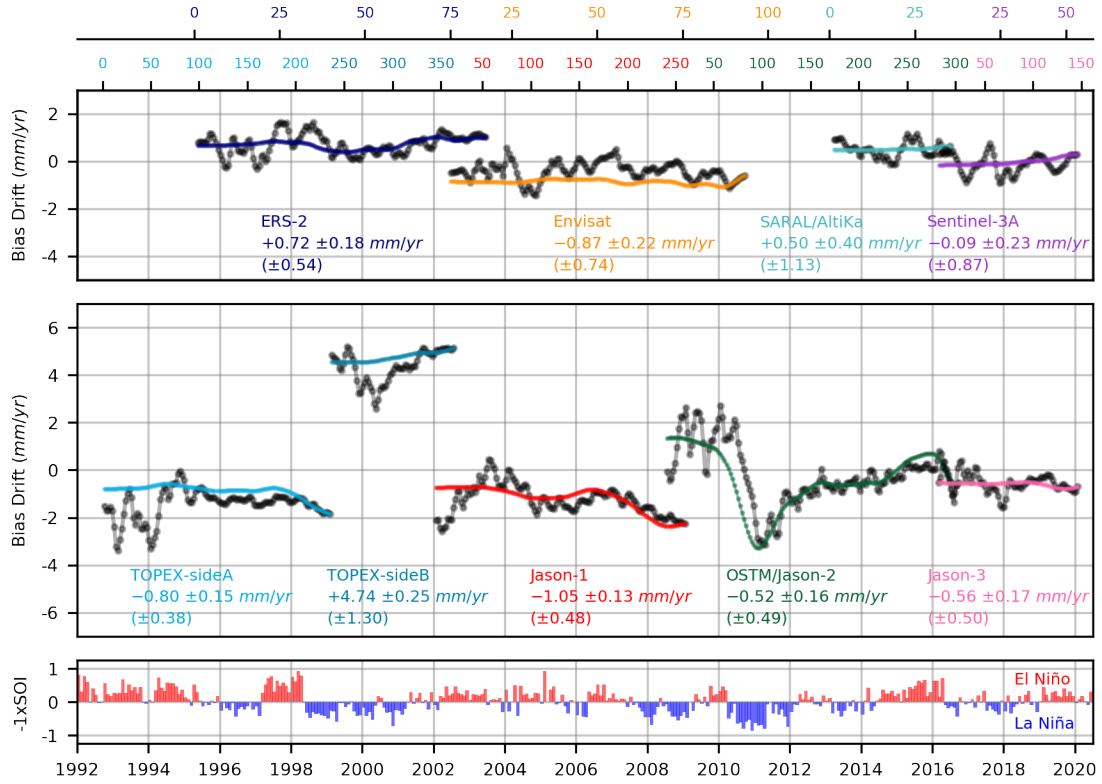


Fig. S31 Mission-specific bias drifts in a solution with Southern Oscillation Index (SOI) introduced as covariates in the ATG observations. The smoothed averages of mission-specific bias drifts are annotated with the 1-sigma uncertainties, scaled by the a posteriori variance factor. The filtering uncertainties are given in brackets. For comparison, the sign-inversed SOI is shown in the lower panel.

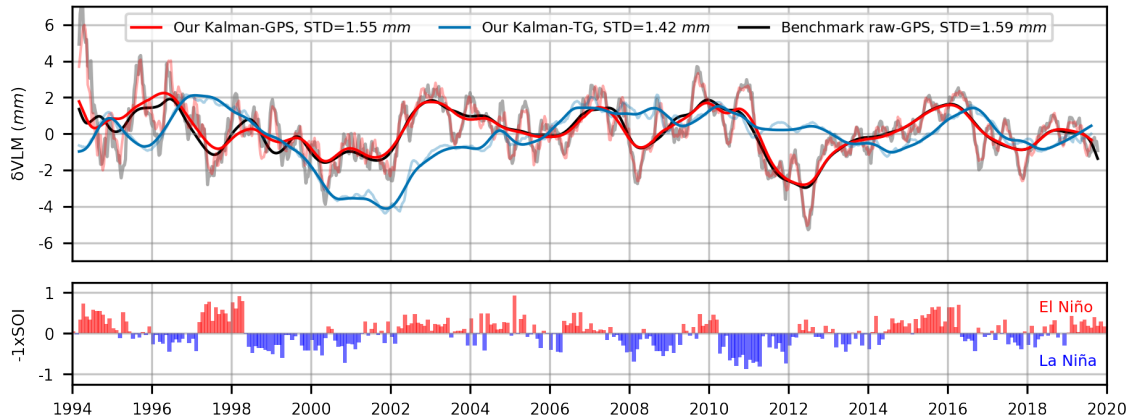


Fig. S32 Weighted average stack of our estimates of nonlinear VLMs at TGs (red line) around the Australian coast from Solution 3 against coastal GPS sites (blue line), in a scenario when the Southern Oscillation Index (SOI) introduced as the covariates in the ATG observations. For comparison, SOI with the sign reversed is shown in the lower panel as the climatic descriptor in the region. The standard deviations (STDs) of the stacked series are annotated.

This investigation further shows small differences in the nonlinear VLM stacks with respect to our preferred solution in the NE, SE, SW, and NW sub-regions (compare Figs. S33-S36 with Figs. S8-S11).

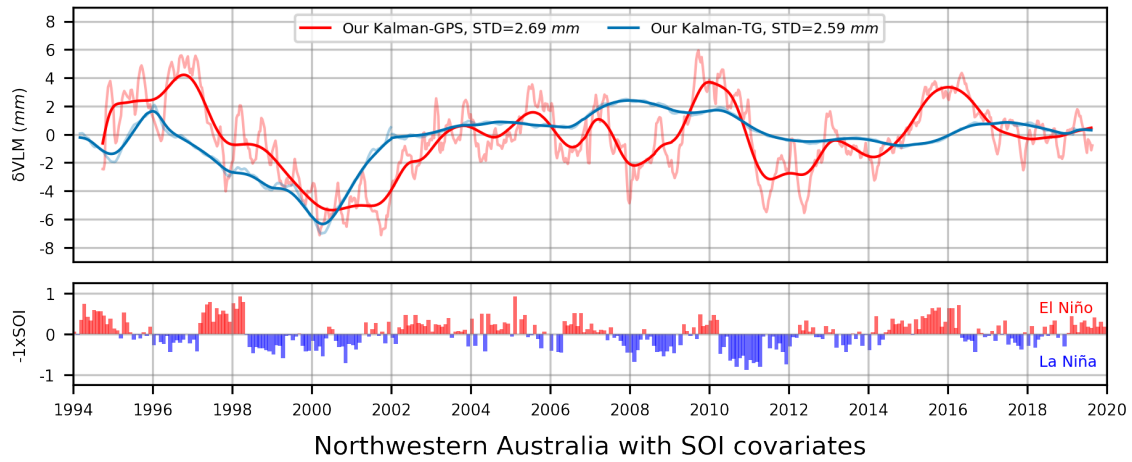


Fig. S33 Weighted average stack of our estimates of time-variable VLMs at tide gauges (TGs, blue line) and coastal Global Positioning System (GPS) sites (red line) from Solution 3 in the NW sub-region, in a scenario when the Southern Oscillation Index (SOI) introduced as the covariates in the ATG observations. For comparison, SOI with the sign reversed is shown in the lower panel as the climatic descriptor in the region. The standard deviations (STDs) of the stacked series are annotated.

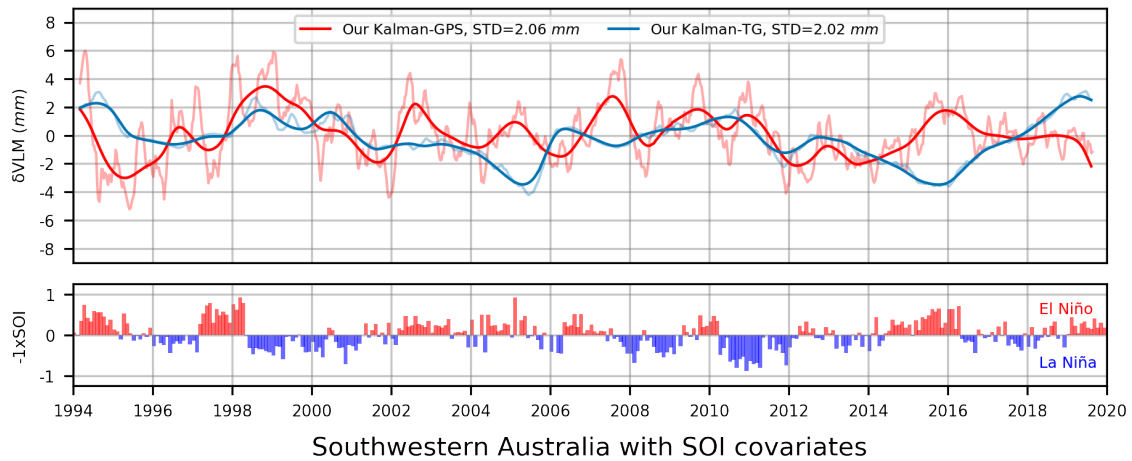


Fig. S34 Same as Fig. S33, but for the SW sub-region.

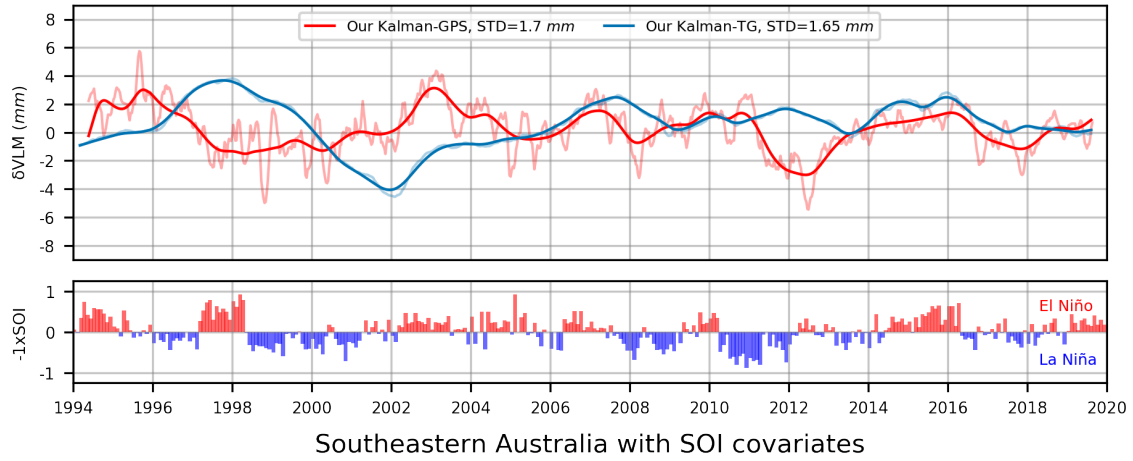


Fig. S35 Same as Fig. S33, but for the SE sub-region.

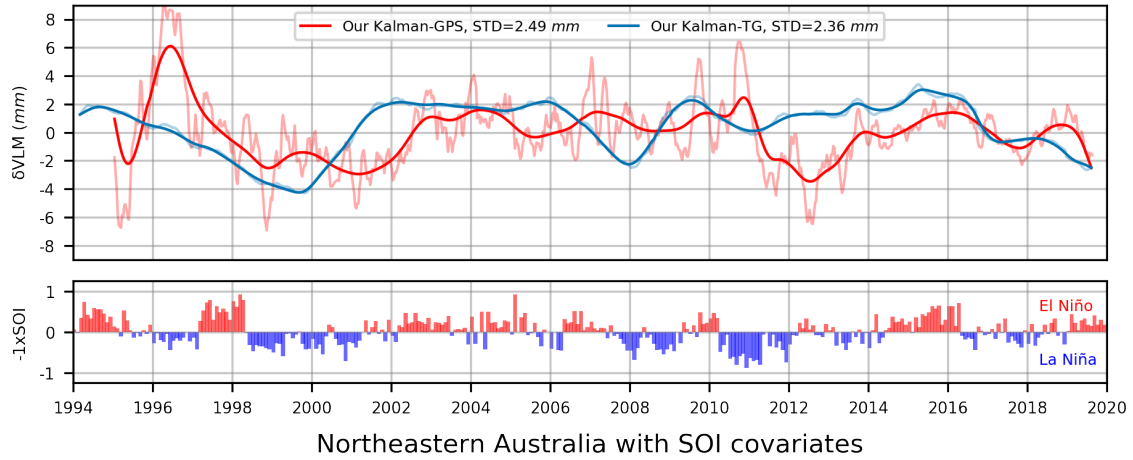


Fig. S36 Same as Fig. S33, but for the NE sub-region.

The consistency between these results with the preferred solution suggest that the ENSO-related variabilities were quite captured in the “white plus AR1” ATG residuals. We noticed some correlations, ranging from -0.02 and -0.73 , between the SOI and the “white plus AR1” ATG residuals.

Overall, this experiment cannot definitively eliminate the alternate hypothesis that the ENSO-related signals somehow leaked into the altimeter systematic errors, instead of being captured in the linear nonlinear components of VLM at the TG locations – this remains for further investigation.

S2.4.5 Impact of zero-drift assumption

Finally, we assessed the impact of the conventional assumption of zero bias drifts on our estimates of the linear VLMs, ASL rates, and nonlinear VLMs at the TG locations. We ran our multi-stage solution approach with the systematic errors constrained to be zero across all missions. The resultant estimates of time-fixed VLM showed marginally greater scatter (0.64 versus 0.56 mm/year), per our preferred solution. As expected, we also noticed an increase in the variability of nonlinear VLM stack at the TGs with a STD of 2.37 mm (compare Fig. 5 with Fig. S37), given the anomalous behaviour of Jason-2 drift in the period of 2010-12 shown in Fig. 6.

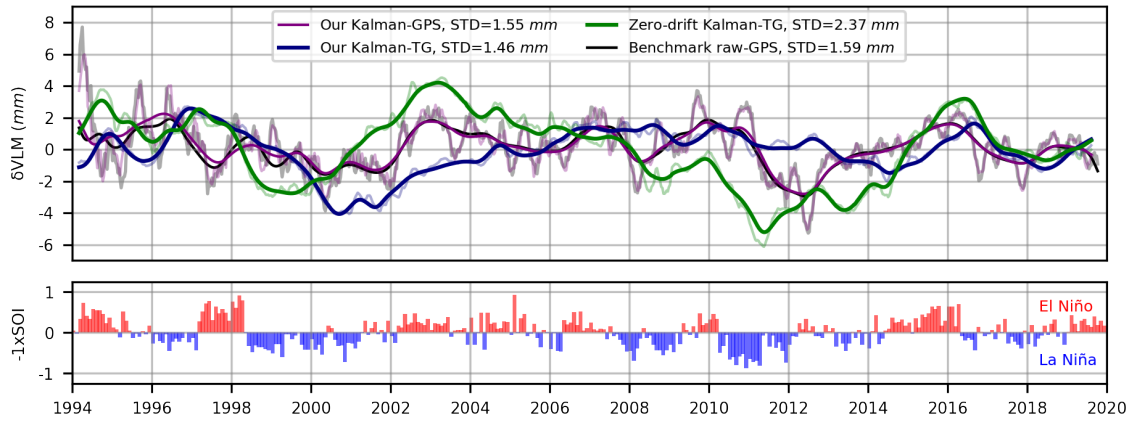


Fig. S37 Weighted average stack of our estimates of nonlinear TG VLM from the scenario when a conventional assumption of “zero-drift” imposed across all missions in the altimetry span (green line), our preferred multi-mission solution (blue line), and coastal GPS sites (purple line) around the Australian continent, with respect to the control stack derived from detrended GPS height series (black line). For comparison, Southern Oscillation Index (SOI) with the sign reversed is shown in the lower panel as the climatic descriptor in the region. The standard deviations (STDs) of the stacked series are annotated.

The average ASL rate is thus slightly underestimated by ~ 0.08 mm/year when the bias drifts were discarded ($+3.32 \pm 0.38$ mm/year versus $+3.40 \pm 0.34$ mm/year), suggesting a negligible effect on monitoring the sea-level rise around the region (Fig. S38).

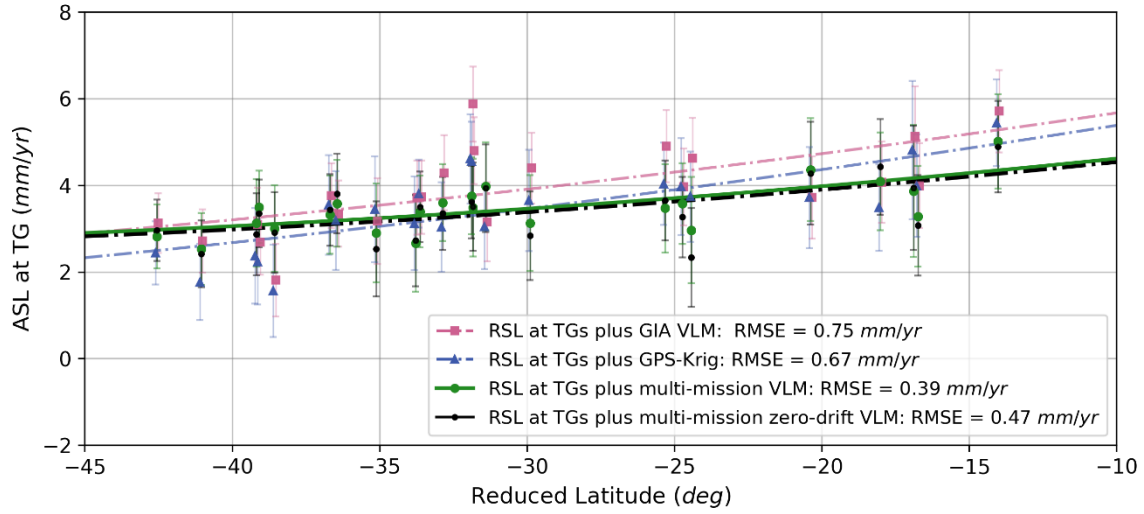


Fig. S38 Profile of ASL trends at TGs by latitude, comparing estimates derived using multi-mission VLMs from a solution when the “zero-drift” assumption imposed (black circles) with our multi-mission VLM (green circles), GPS-Krig (blue triangles) and ICE6G_D GIA (pink squares) trends. Solid and dashed lines show a quadratic polynomial fitted to each set of ASL estimates per latitude reduced to the SE-NW direction, with root mean squared error (RMSE) about this fit annotated in the legend. For clarity, TG latitudes at STON and CARN locations are shifted by -0.75 degrees, and TG latitudes at PORT, ESPE, HILL, THEV and TOWN are shifted by $+0.75$ degrees. The latitudes of TGs where ASL is derived from GIA and GPS-Krig are also shifted by $+0.045$ and -0.045 degrees, respectively. Error bars are ± 1 -sigma scaled by the a posteriori variance factor.

S2.5 Implications for the approach: differential oceanography

We computed the distances between the comparison points (CPs) and the coast, and the separations of CPs from TGs for ATG combinations between each pair of TG and CP, pertaining to either the Jason-series, Envisat-series or Sentinel-3A constellations (Fig. S39). Comparing these with the variability of the magnitudes of nonlinear VLM and ATG noise, shown in Fig. 10 of the main manuscript) reveal the correlation was increased as a function of CP distances from either TGs or the coast, though this becomes more pronounced as a function of the coast-CP separation. These further suggest the potential presence of residual oceanographic signals, especially for the cases where CPs were located off the shelf (defined as the 200 m depth contour).

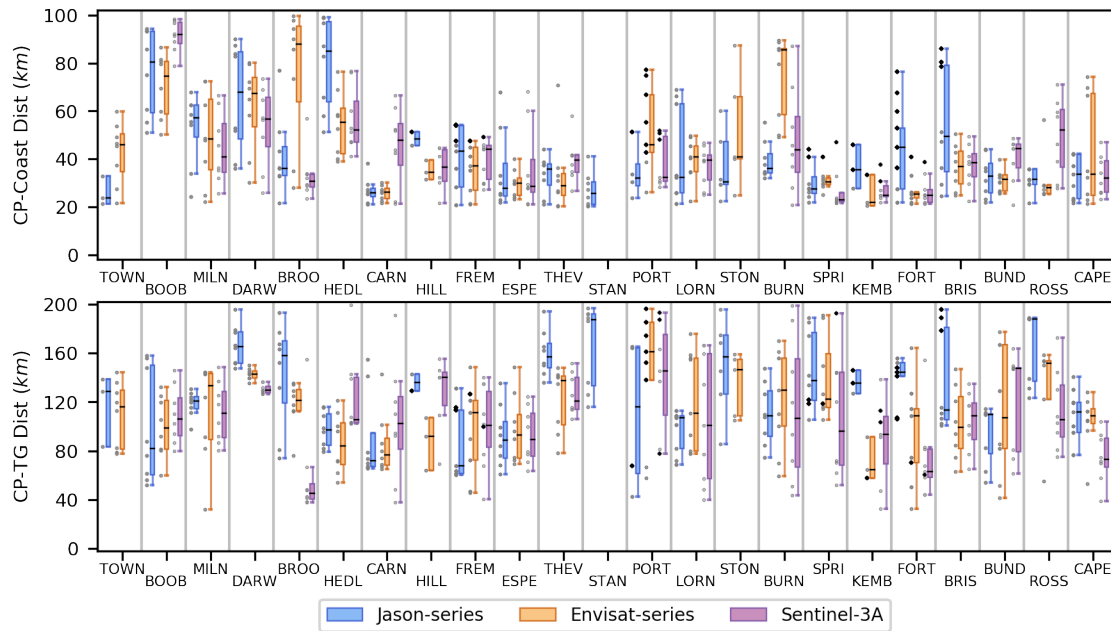


Fig. S39 Spatial variability in (top) distances between comparison points (CPs) and the coast, and (bottom) separations of CPs from TGs, pertaining to the Jason-series (blue), Envisat-series (orange) and Sentinel-3A (purple) constellations on a per TG basis. Note the different scales on y-axes. CPs located “on” and “off” the continental shelf are differentiated with grey and bolder black dots. TGs are ordered anti-clockwise around the Australian coast, commencing with TOWN located on the North-East region.

S2.6 Residuals and a posteriori analysis

We explored how well the filtering and smoothing perform in terms of separating the closely-correlated parameters in the underlying problem. We evaluated a posteriori estimates of unknowns and ATG residuals in each solution of the multi-stage approach. To check the convergence between filtering and smoothing estimates, we inspected our estimates of unknown parameters corresponded to an individual ATG combination (that include intercept specific to a TG/CP pair, time-fixed and time-variable components of VLM specific to a TG, and across-track ASL slope specific to a CP) over the satellite altimetry span.

Figure S40 shows the estimates of ATG intercept series for a representative CP nearby the BURN TG, whereas Figs. S41 and S42 represent the estimates of linear and nonlinear components of VLM pertaining to this gauge location in each solution (the iteration) of our multi-stage approach. From comparing these figures, the ATG intercepts from Solution 1 fluctuated in time (treated as a time-variable quantity to capture the residual variability due to either the difference between spatially interpolated GPS-Krig and actual VLM values or the presence of localized nonlinearity), but the TG VLM trend was fixed in time considering the tight constraints. In contrast, the ATG intercepts were estimated as time-fixed unknowns in the subsequent solutions, while the TG VLM could vary in time. This approach enabled ensuring the appropriate decorrelation between our output parameters, such that the unmodeled signals were well captured into the optimal estimates of the nonlinearity in VLM and bias drift parameters in the final solution.

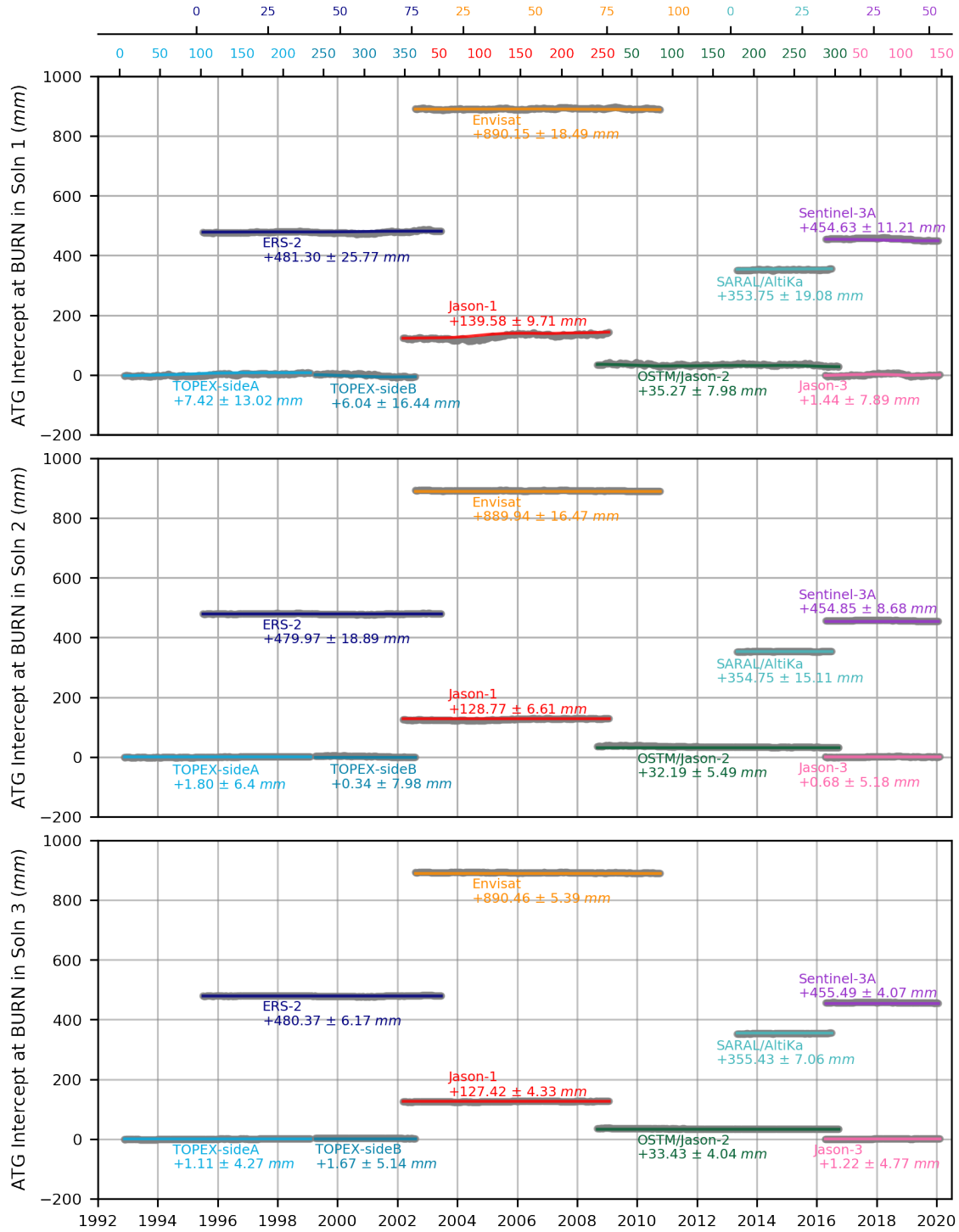


Fig. S40 Cycle-by-cycle estimate of ATG intercepts for a representative CP in the vicinity of BURN TG in the final iterations of (top) Solution 1, (middle) Solution 2 and (bottom) Solution 3 within our multi-stage approach. The grey lines show the forward filtering estimates, while the colored lines show the return smoothing results. The estimated intercepts loosely varied in time in Solution 1 due to the unmodeled signals, while treated as time-fixed quantities in the subsequent Solutions 2 and 3. The averaged smoothing estimates are annotated for each solution, with the 1-sigma uncertainties that have been scaled by the a posteriori variance factor. Note all intercepts are relative to the median estimate of TOPEX-side A in each solution.

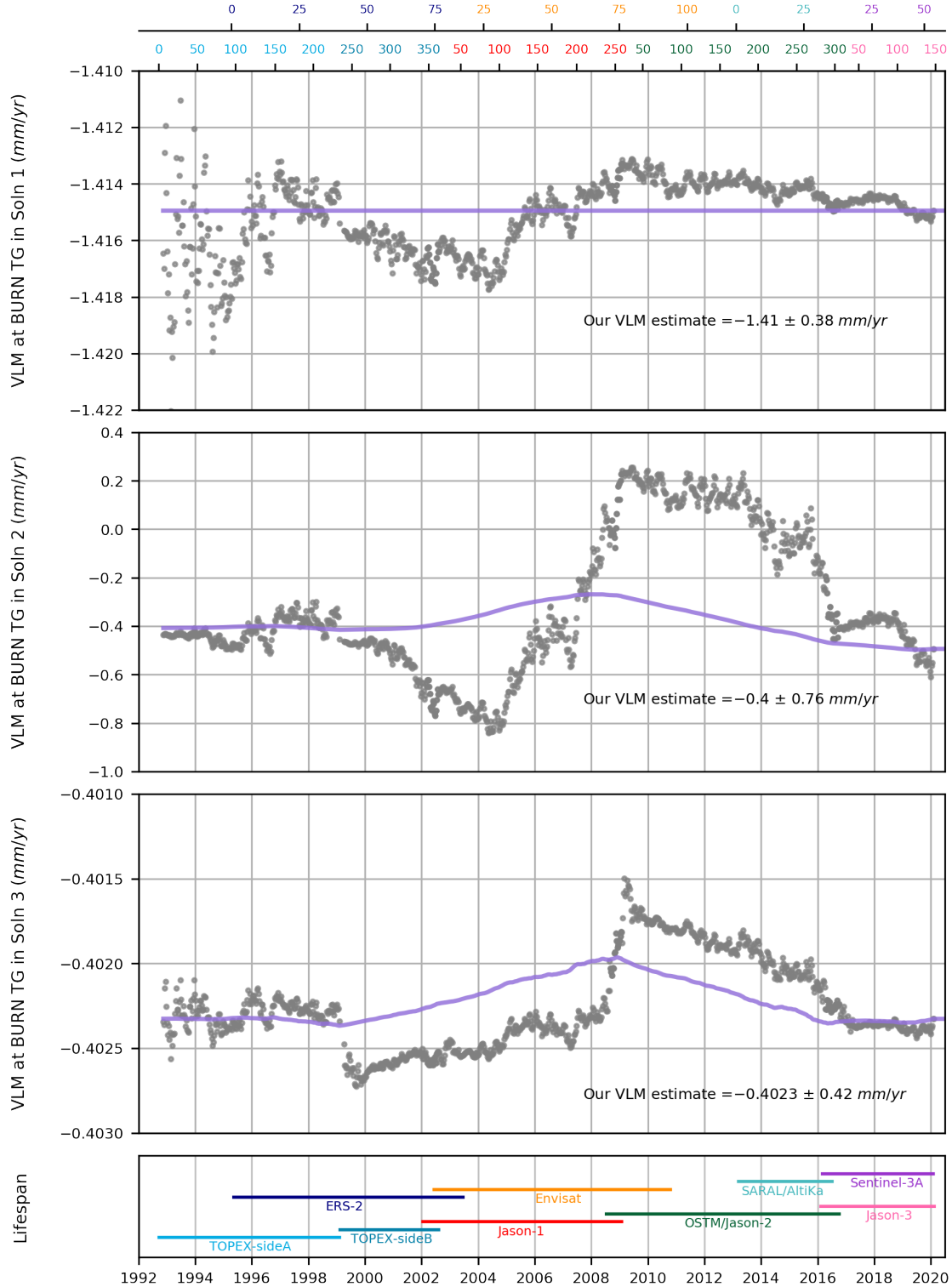


Fig. S41 Cycle-by-cycle estimates of time-fixed VLM at BURN TG in the final iterations of (top) Solution 1, (middle) Solution 2 and (bottom) Solution 3 within our multi-stage approach. The mission lifespans are illustrated at the bottom. The grey dots show the forward filtering estimates, while the purple lines show the return smoothing results. Note the very different scales on y-axes to emphasize the level of constraint imposed. The annotated values are the weighted averages of smoother estimates from each solution, with the 1-sigma uncertainties that have been scaled by the a posteriori variance factor.

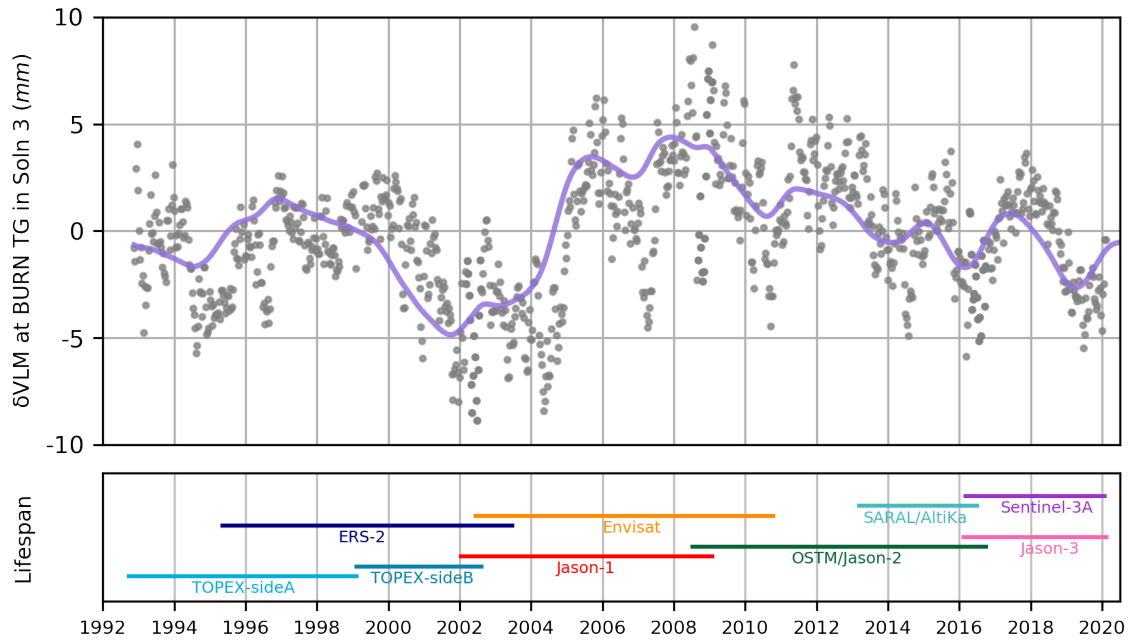


Fig. S42 Cycle-by-cycle estimates of time-variable VLM at BURN TG derived from the final iterations of Solution 3 within our multi-stage approach. The mission lifespans are illustrated in the lower panel. The grey dots show the forward filtering estimates, while the purple line shows the return smoothing results.

Figure S43 shows the estimates of the across-track ASL slope for this representative CP derived from the different solutions of the multi-stage approach. As shown, our estimates in Solution 1 slightly deviated from a priori value inferred from the DTU15 mean sea surface (MSS) model, whereas in Solutions 2 and 3 we see improvements in the convergence of our filtering and smoothing estimates.

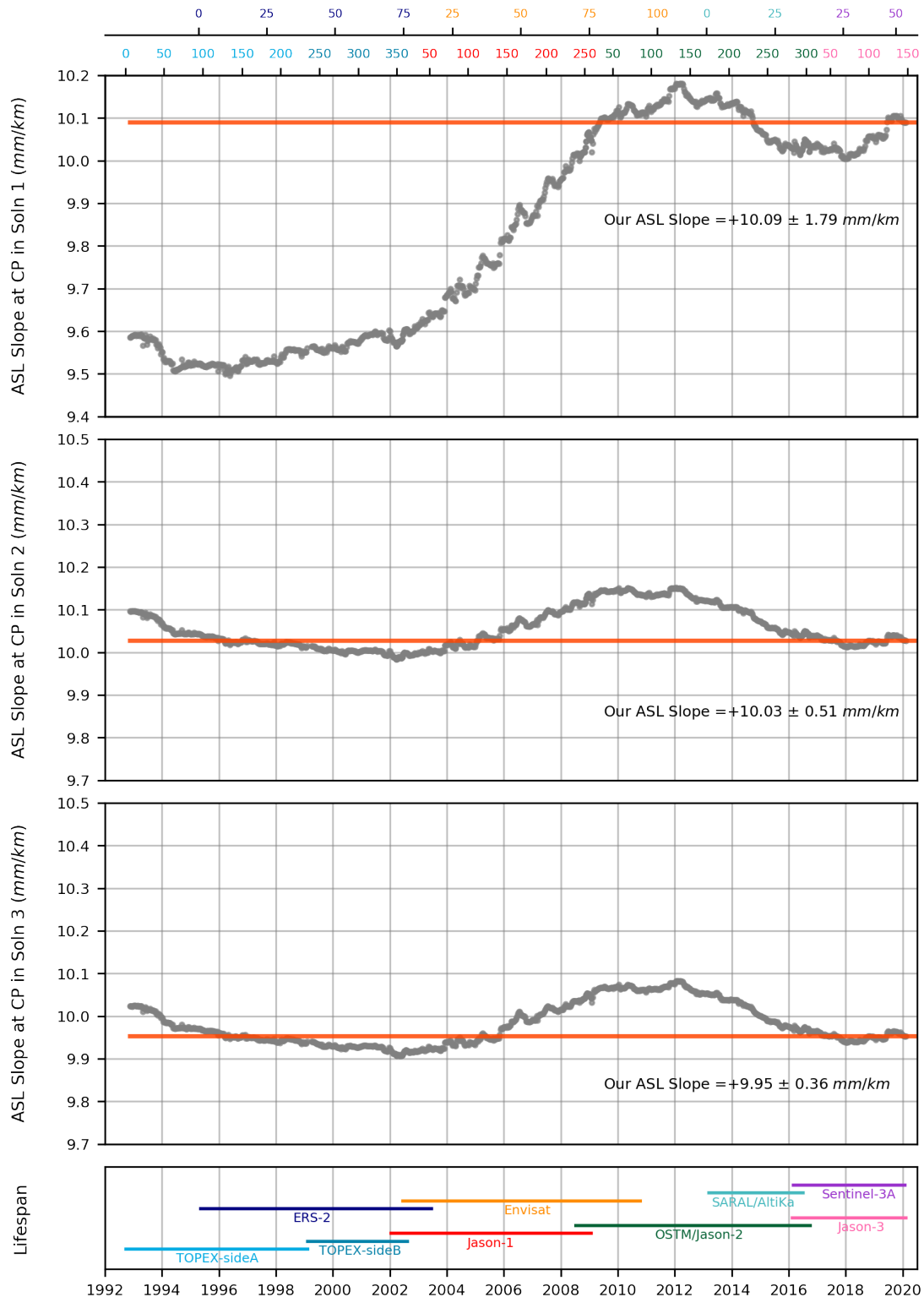


Fig. S43 Cycle-by-cycle estimates of ASL slope for a representative CP in the vicinity of BURN TG in the final iterations of (top) Solution 1, (middle) Solution 2 and (bottom) Solution 3 within our multi-stage approach. The mission lifespans are illustrated at the bottom. The grey dots show the forward filtering estimates, while the orange lines show the return smoothing results. Note different scales on y-axes. The annotated values are the weighted averages of smoother estimates from each solution, with the 1-sigma uncertainties that have been scaled by the a posteriori variance factor.

Further, we monitored the cycle-by-cycle weighted average of “white plus AR1” residuals of ATG observations on a per TG basis, considering all CPs associated with any given TG, in different stages of our multi-stage approach to detect suspicious gauge records with unmodeled signals/behaviour. Within this process, we visually inspected the ATG residuals pertaining to a TG relative to the nearby gauges as well as the stack of all ATG residuals over the region.

An important check here is to ensure that the slopes of the weighted residuals of individual TGs are zero, otherwise TGs with unmodeled signals would be detected and flagged for further investigations. For instance, Figs. S44 and S45 respectively show the assessment results for the non-reference and reference ATG combinations specific to the BURN TG in the subsequent solutions.

Note there is a good agreement between this ATG residual analysis with that derived from stacking all TG residuals over the region (see Fig. 12 in the main paper), suggesting the datum stability of the TG records. In comparison with similar analysis for other gauges nearby the BURN TG, no suspicious RSL datum issue was detected as well.

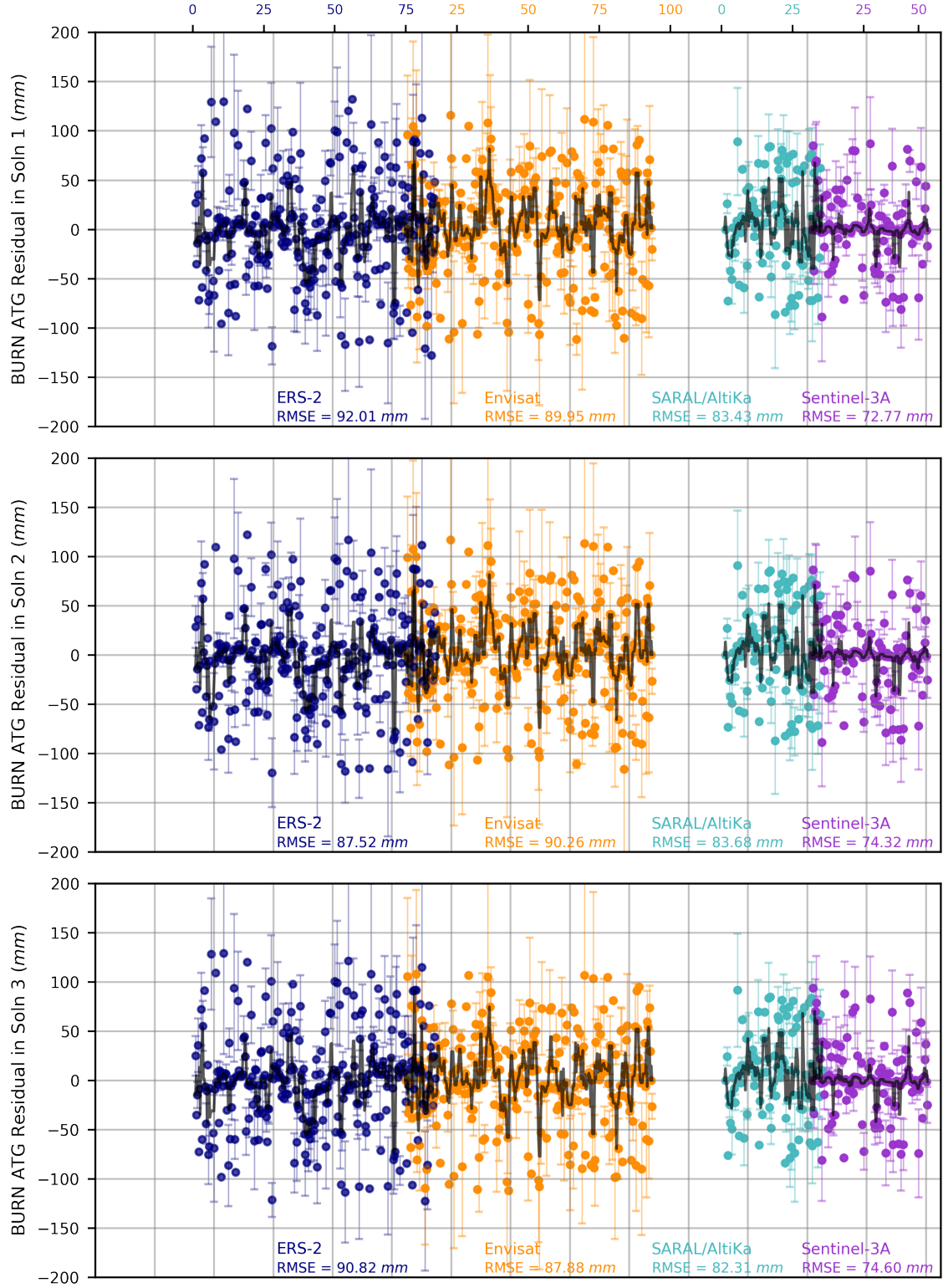


Fig. S44 Cycle-by-cycle weighted average of “white plus AR1” residuals of non-reference ATG combinations specific to BURN TG in the final iterations of (top) Solution 1, (middle) Solution 2 and (bottom) Solution 3 within our multi-stage approach, with root mean squared error (RMSE) of mission-specific noise annotated. The observational cycles of non-reference satellites are shown on the top axis with the same colours.

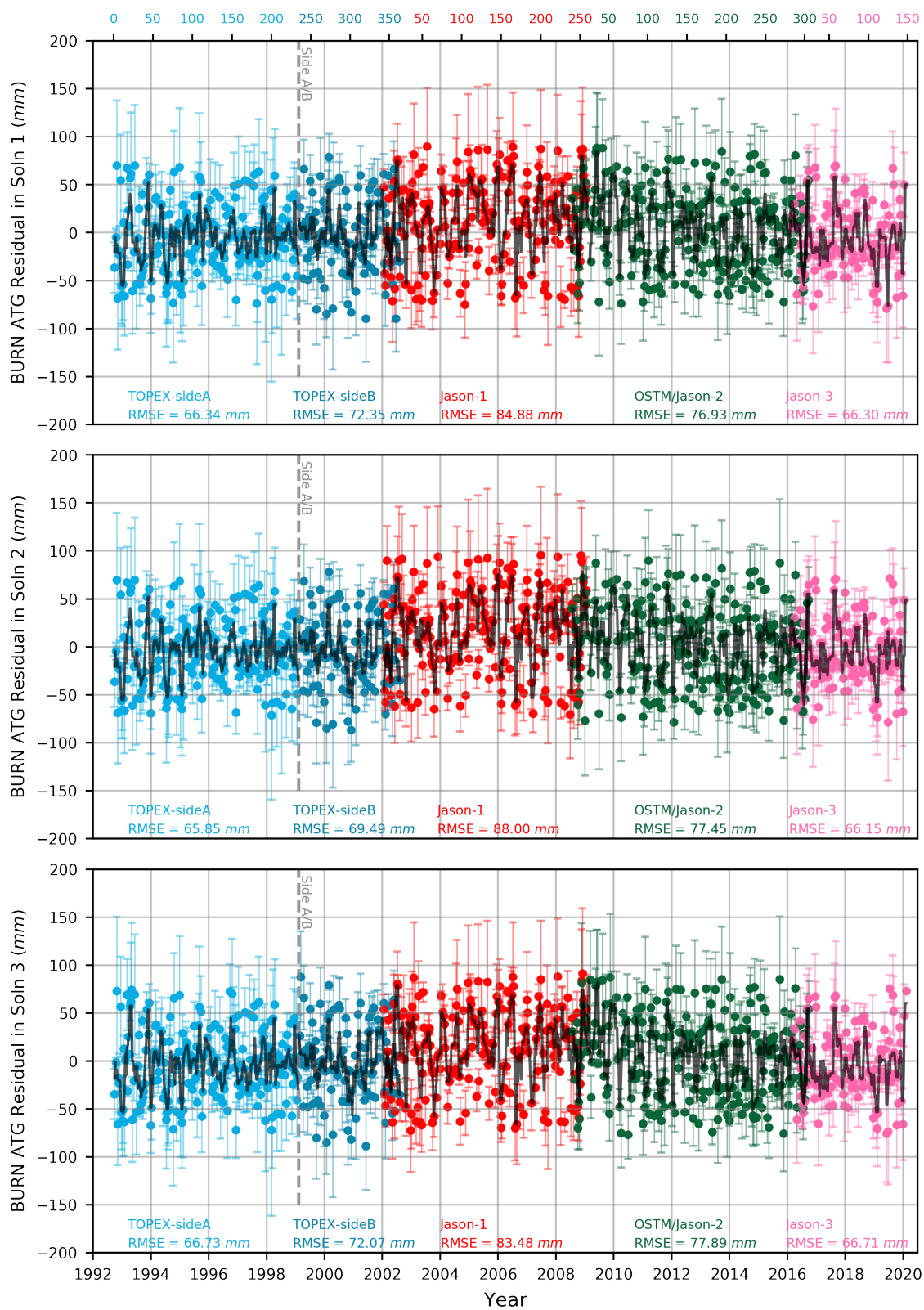


Fig. S45 Same as for Fig. S44, but for ATG observations associated with the reference-mission series.

We further evaluated the performance of the method through a suite of sanity checks. We probed any plausible disturbances present in our final estimates of the ATG intercept and the TG VLM datum from Solution 3 to investigate the presence of uncaptured signals. For the estimated ATG intercepts, we removed the median of each intercept series and then made a cycle-by-cycle weighted average of all median-removed intercepts over the study region. These weighted averages were constantly zero in the satellite era, which indicate our final estimates of ATG intercept are robust for subsequent analysis; that would otherwise be contaminated with unfavourable trends if they were unsuccessfully decoupled from the bias drift estimates.

For detecting plausible disturbances in the TG VLM datum, we derived cycle-by-cycle weighted averages of VLM trends at TGs located around Australia to check any fluctuations of our time-varying estimates of VLM datum across the altimetry span which could lead to potentially erroneous estimates of bias drift. Figure S46 indicates that there is no evidence of spatially-correlated common-mode errors in TG VLM estimates, that would possibly present as a side effect of improper decorrelation from the altimeter bias drifts. This added confidence to our interpretation of the possibility of significant systematic errors present in the altimetry dataset around Australian region.

We finally checked the spatial variability of our estimates of across-track ASL slope from Solution 3, versus the a priori values taken from the DTU15 MSS model. As shown in Fig. S47, there is a good level of spatial coherence for the ASL slope estimates over the study region, consistent with that from the a priori values. We found negligible differences between the ASL slopes from our approach and the DTU15 MSS model.

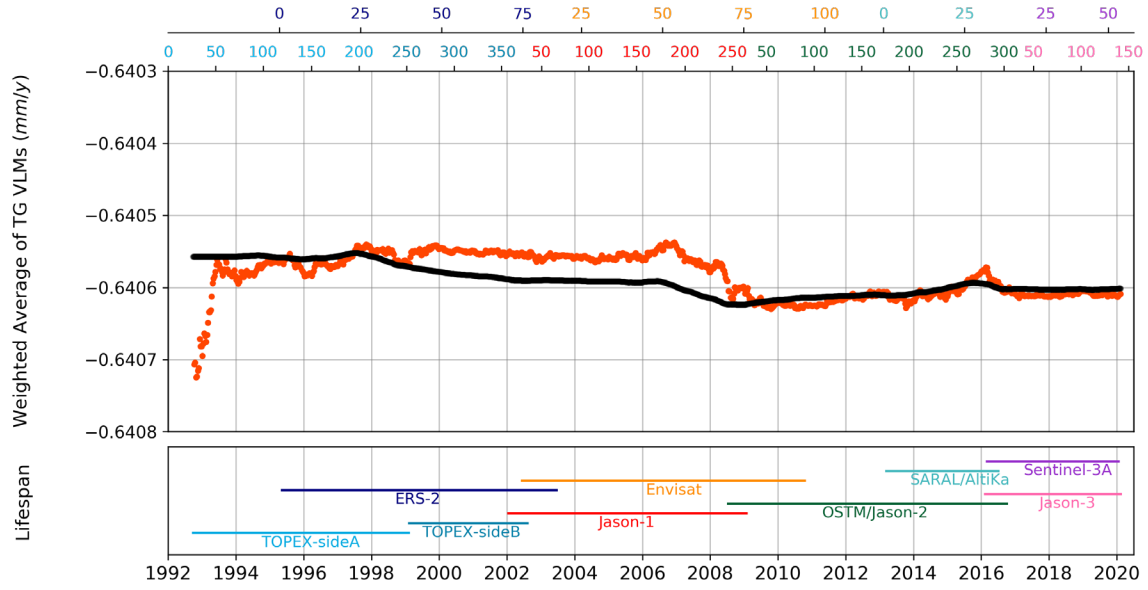


Fig. S46 Cycle-by-cycle weighted averages of time-fixed TG VLM estimated from Solution 3. Note very slight change of the estimates as the indication of stability of our resolved datum in altimetry era. The mission-specific timespans are illustrated in the lower panel.

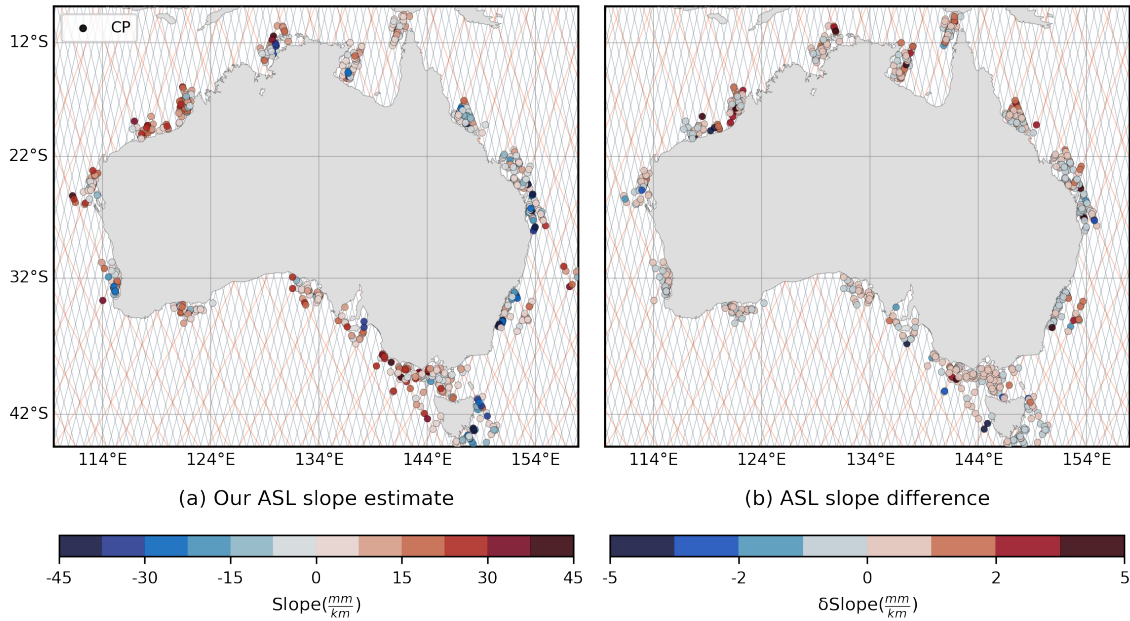


Fig. S47 Map of (a) our ASL slope estimates, and (b) ASL slope differences, DTU15 MSS-derived a priori values subtracted from our results. Note the negligible differences between a priori and a posteriori ASL slopes. The ground tracks of Jason-series and Envisat-series altimeters are shown in orange and grey, respectively. Note the different colour scales in (a) and (b).

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