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New tide gauges cross-calibration method : multi-instrument data combination

Application to a multi-instrument experiment carried out in 2016 by SONEL*, SHOM** & LIENSs^a teams on the Aix island, France.

Tide gauges calibration

Studies about sea level change at the coast require high quality sea level time series. The main source of sea level measurements is presently provided by digital coastal tide gauges. Calibration campaigns are regularly carried out to ensure their precisions & accuracies. Several types of sea level sensors exist – tide pole, probe, radar tide gauge, pressure tide gauge, GNSS buoys, GNSS reflectometry – but their field performances are usually unknown. We show that a new calibration method can take advantage of simultaneous measurements to better assess sensors biases but also estimate the uncertainty associated with each sensor.

Most common tide gauge errors

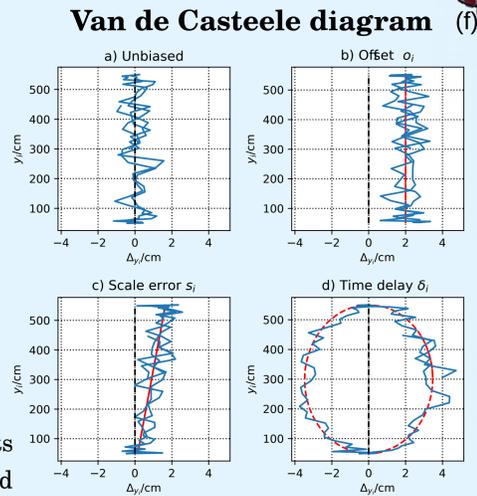
Observed sea level : $y_i(t) = SSH(t - \delta_i) \times (1 + s_i) + o_i + e_i(t)$

- The **time delays** (δ_i) are non linear biases that are usually estimated and corrected by maximizing the cross-correlation between 2 sea level signals.
- The **offsets** (o_i) are constant error.
- The **scale error** (s_i) are errors proportional to $y_i(t)$.
- The **residuals** (e_i) are stochastic measurement errors.

Difference-based methods

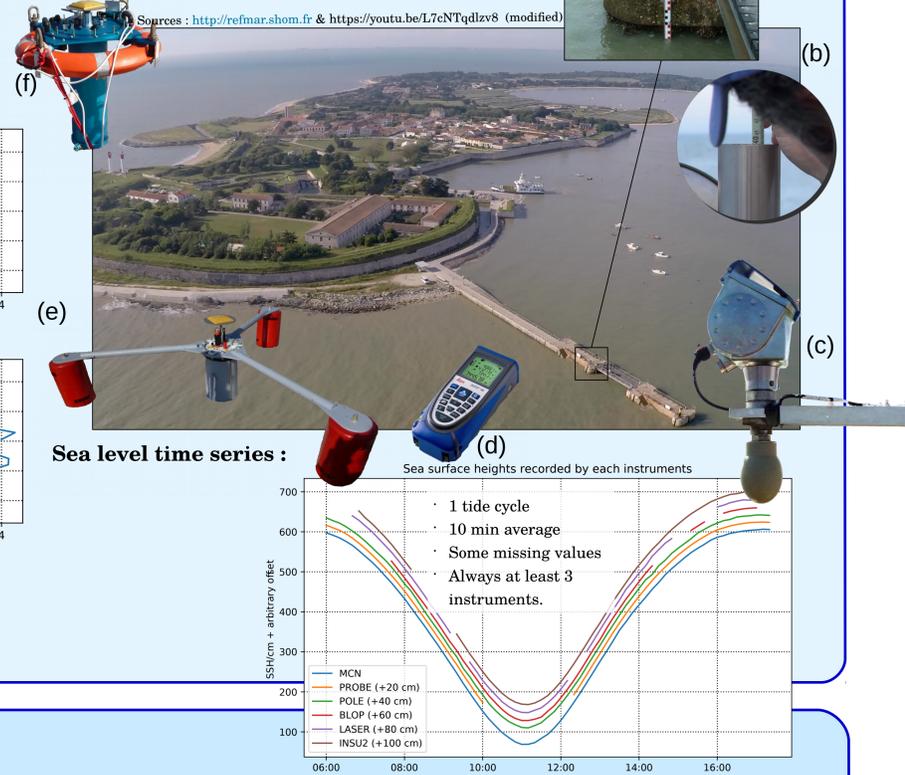
$$\Delta_{y_i}(t) = y_i(t) - y_{ref}(t) = y_i(t) \times s_i + o_i + e_i(t)$$

An example is the **Van de Castele diagram**. It consists in analysing the sea level difference between one tested instrument and a reference instrument. A linear regression on the differences gives offset and scale error estimates. However, this method only works for a pair of sensors.



Aix island experiment - 6 instruments / 11 h records

- POLE** : Tide pole (a)
- PROBE** : Probe (b)
- MCN** : Radar digital tide gauge (c)
- LASER** : Distance meter (d)
- INSU2** : GNSS buoy (e)
- BLOP** : GNSS buoy (f)



Proposed method – A combination-based method

If more than 2 sensors : a combination is possible.

The main idea is to compare all sensor time series to a more reliable and more complete combined sea level signal, which is an average \bar{h} of all corrected sea level time series, weighted by their unknown precisions. First, we build a stacked observations vector of p instruments (1). Then, we define a linear parametric stochastic model Q_y (2) and a linear parametric functional model (3) such as :

$$\vec{y} = \begin{pmatrix} \vec{y}_1 \\ \vdots \\ \vec{y}_i \\ \vdots \\ \vec{y}_p \end{pmatrix} \quad (1) \quad Q_y = \sigma_1^2 Q_1 + \sigma_2^2 Q_2 + \dots + \sigma_p^2 Q_p \quad (2)$$

Noise model,
linearly independent
matrices Q_i

$$(3) \quad \vec{y}_i = \begin{cases} \vec{h} + \vec{e}_i & \text{if the } i\text{-th sensor is unbiased} \\ \vec{h} + \vec{y}_i \times s_i + o_i + \vec{e}_i & \text{otherwise} \end{cases}$$

Unknowns : Combined signal (h) + Biases (o, s) + Instrument precisions (σ) : $\vec{x} = \begin{pmatrix} \vec{h} \\ \vec{o} \\ \vec{s} \end{pmatrix} \quad \vec{\sigma}^2 = \begin{pmatrix} \sigma_1^2 \\ \vdots \\ \sigma_p^2 \end{pmatrix}$ } **Estimated using Least-Squares Variance Component Estimation (LS-VCE) [Teunissen and Amiri-Simkooei, 2008]**

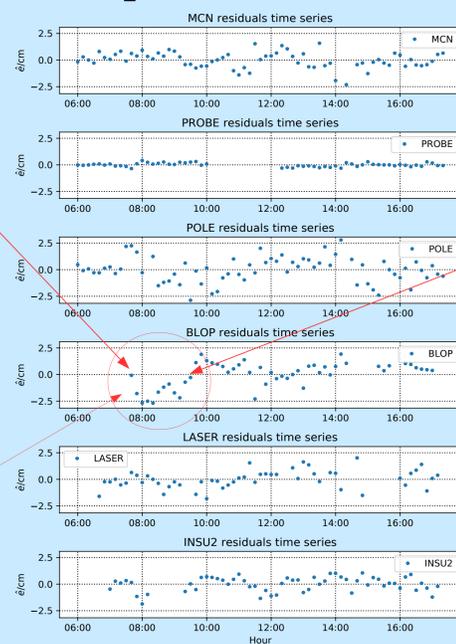
A more complete assessment of sensor performances

We applied the new method to the Aix island experiment.

To avoid an ill-posed problem, PROBE was assumed unbiased, allowing to assess the offsets, scale errors of other sensors and the uncertainties of all sensors.

The residuals time series help to understand the poor performance of BLOP : a 2 h mean shift was detected !

TG	o (cm)	s (cm/m)	σ (cm)
PROBE	.	.	0.31 +/- 0.10
MCN	-1.87 +/- 0.30	0.52 +/- 0.07	0.81 +/- 0.08
POLE	0.13 +/- 0.39	-0.32 +/- 0.09	1.23 +/- 0.12
BLOP	-4.30 +/- 0.41	0.00 +/- 0.11	1.25 +/- 0.14
LASER	-3.42 +/- 0.35	0.13 +/- 0.08	0.90 +/- 0.10
INSU2	-3.52 +/- 0.30	0.17 +/- 0.07	0.74 +/- 0.09

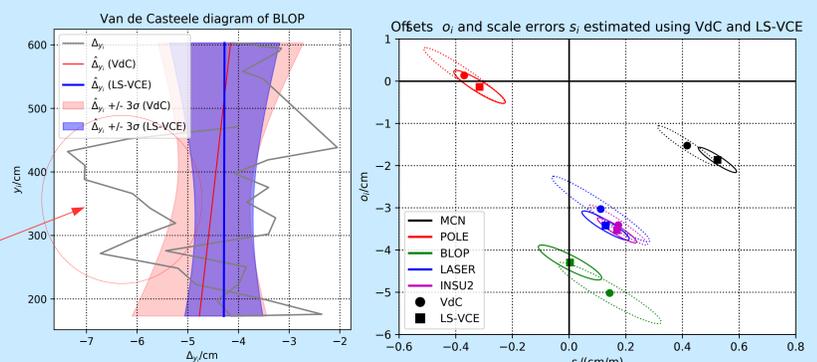


An improved bias estimation

We compared the new results to a difference-based method.

The difference-based methods did not take advantage of the redundancy of information provided by the multi-instrument experiment. Also, when the reference instrument (here PROBE) had missing values, the observations acquired by other instruments at the same time could not be taken into account (i.e. the differences could not be computed).

With the proposed method, all observations have been taken into account because the reference combined signal had no missing values. This improvement reduced the uncertainty of the bias estimates from 30% to 55%. This is clearly visible in the Van de Castele diagram (left) and in parameter space (right) below :



Conclusions

- Pairwise difference-based methods are not suited for multi-instrument calibration campaigns.
- An improved sensor calibration (combined signal + sensor biases + sensor uncertainties) is possible by using a combination formulation of the problem along with a Variance Component Estimation method.
- The better use of all available observation can lead to a reduction of bias uncertainties in case of missing values : here a reduction from 30% to 55%.
- The formulation is flexible and can be extended to longer time series and to altimeter satellite calibration.

Reference :

[Teunissen and Amiri-Simkooei, 2008] Teunissen, P. J. G. and Amiri-Simkooei, A. R. (2008). Least-squares variance component estimation. Journal of Geodesy, 82(2):65–82.

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Experiment in video :

