WP 4.1 NOC/SKYMAT Ltd

Validation with Tide Gauges

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WP 4.1: Aim

To conduct a ‘global’ validation of the coastal altimetry product developed by TUM and LEGOS during this project against observations from a carefully selected set of tide gauges.

The validation will be done in terms of:

- Sea-level annual cycle (amplitude and phase)
- Interannual variability
- Linear trend

WP 4.1 Datasets

Altimetry Products

Supplied TUM/LEGOS along track products, using Jason 1 to 3, Envisat ?

Tide-Gauge Products

High-frequency (e.g., hourly) records from BODC and UHSLC

Monthly mean values from PSMSL and GPS data (http://www.sonel.org)

DAC for tide-gauge data from AVISO

GIA data for both tide-gauge and altimetry data from ICE-6G

Ocean Model Data (1965 to 2015)

Nucleus for European Modelling of the Ocean (NEMO) ORCA N006 is a state-of-the-art modelling framework of ocean related engines. The spatial resolution is 1/12 degree with a monthly temporal resolution.

WP 4.1 : Methodology

- Validation at different timescales is important because the drivers of sea level (SL) change vary with timescale. The implication is that the altimeter's performance might depend on the timescales.
- Similarly, SL changes at different tide-gauge locations might be driven by processes with different length scales. Because altimeter measurements are rarely collocated with tide-gauge sites, the validation will necessarily be better at sites with long length scales.
- The approach followed here will involve:

1. Extract length scales at tide-gauge sites based on NEMO sea level.
2. Group tide-gauge sites according to length scales.
3. Collocation in time of hourly tide-gauge records with altimeter data (similar to Calafat et al., 2017; Passaro et al., 2018).
4. Comparison in terms of sea-level annual cycle, inter-annual variability, and trends, as function of distance to the coast (and tide gauge).

Bayesian AR1 regression model for annual cycles trends

Trends and annual amplitude/phase are computed using a regression model with errors assumed to follow an AR1 process. We adopt a Bayesian approach, thus modelling the unknown parameters as random variables.

$$y_t = \beta x_t + e_t$$

$$e_t = \rho e_{t-1} + u_t \,, \qquad u_t \sim \mathcal{N}(0, \sigma^2)$$

$$\theta = (\beta, \rho, \sigma^2)$$ ← Unknown parameters, including trend

$$p(\theta | y_{1:T})$$ ← Posterior distribution (what we sample from)

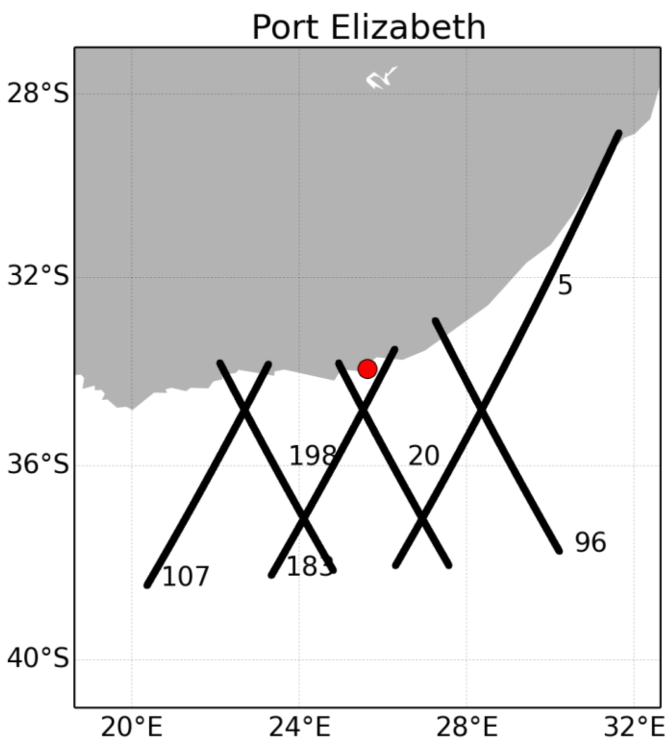
Advantages

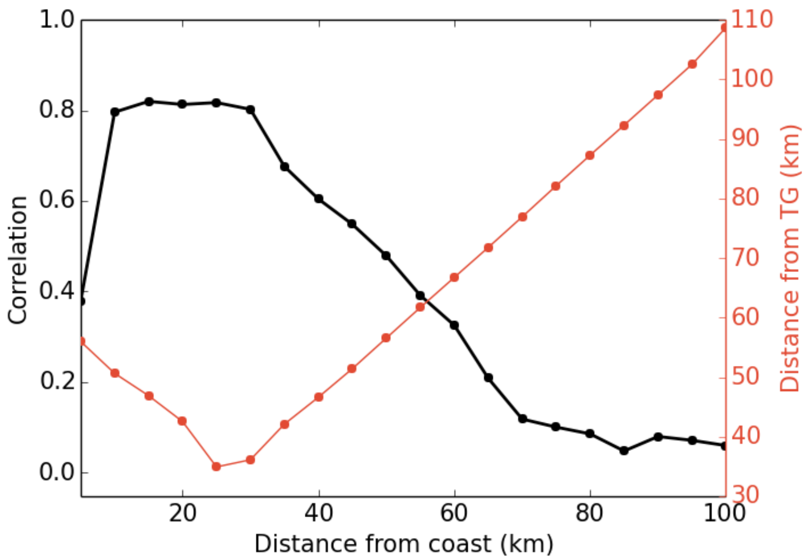
It provides more realistic standard errors

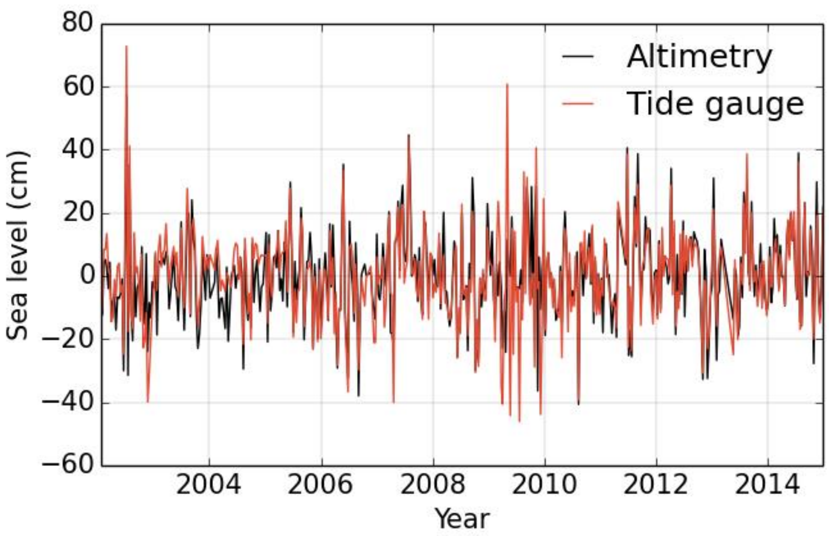
In the presence of serial correlation, this estimator is more efficient than OLS (i.e., trend estimates are more precise)

Computing standard errors for any function of the parameters is straightforward (e.g., amplitude/phase of the annual cycle)

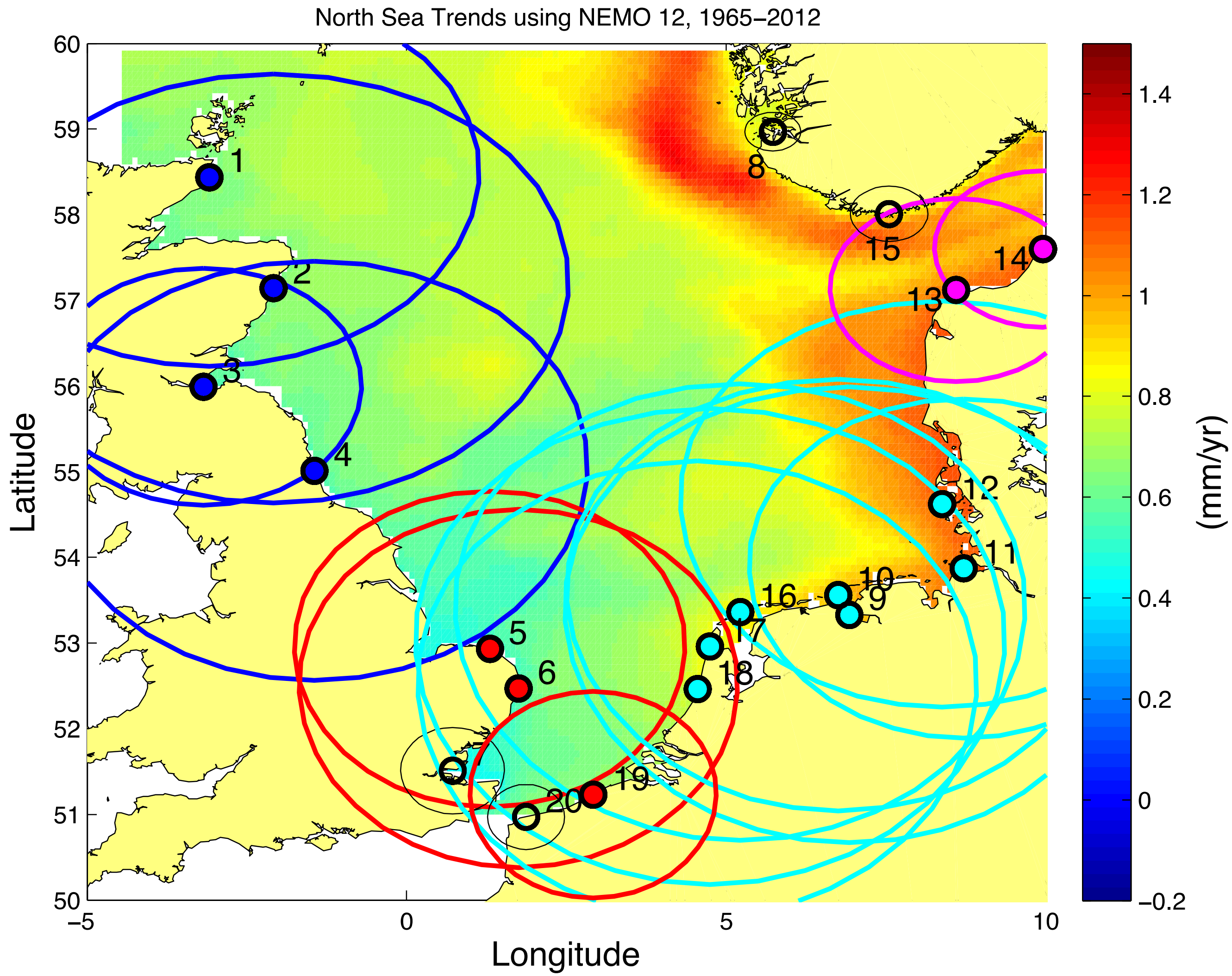
Example of interannual validation



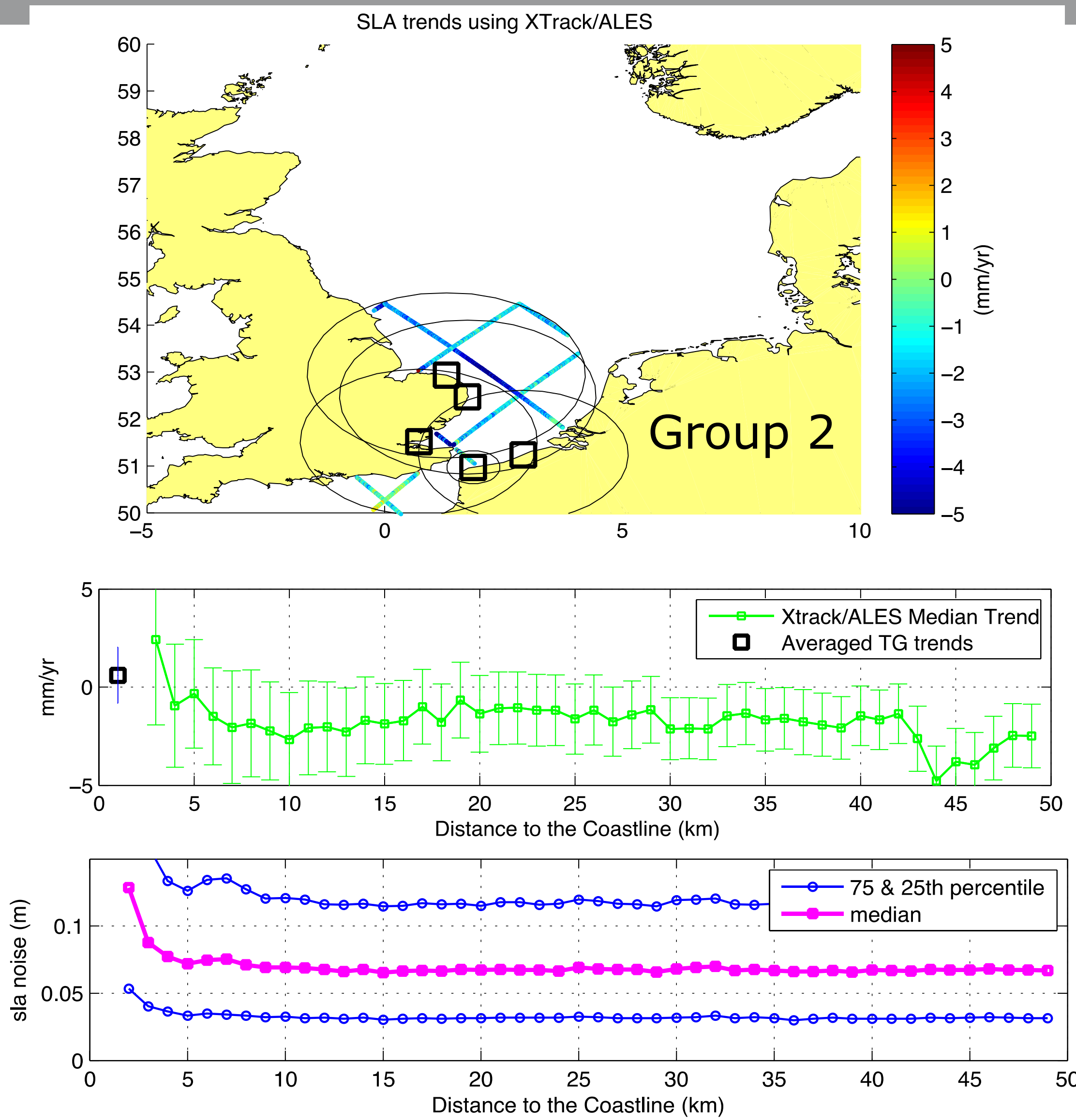




Example of grouping the TGs based on decorrelation length scales in the North Sea



Results : SL_cci BP; LS based on NEMO



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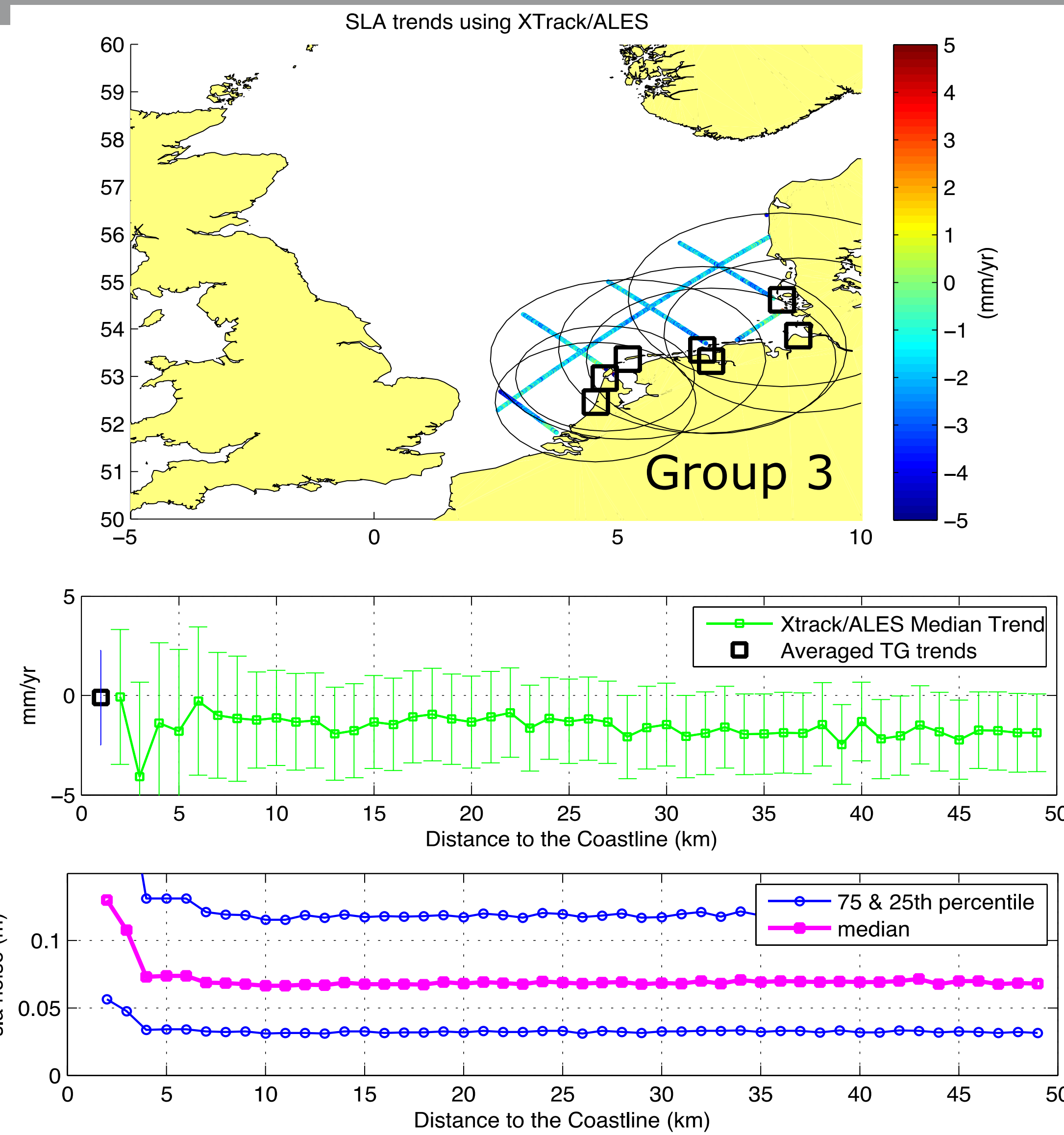

Summary: SL_cci Bridging Phase of trends (mm/yr) from Tide Gauges and altimetry Xtrack/ALES.

	The North Sea (2002 to 2016)		
	TG Trends mm/yr	Xtrack/ALES mm/yr	Optimal Distance to the coast(km)
Group 1	-0.28 ± 1.31	-2.40 ± 4.43	4
Group 2	0.60 ± 1.43	-0.95 ± 3.14	4
Group 3	-0.11 ± 2.38	-1.39 ± 4.04	4
Group 4	-0.02 ± 3.82	-0.56 ± 2.45	5
	The Mediterranean Sea (2002 to 2016)		
Group 1	1.30 ± 1.35	0.01 ± 1.54	4
Group 3	4.12 ± 0.91	0.71± 2.05	4
Group 4	4.78 ± 2.44	2.09 ± 1.32	4
Group 5	5.78 ± 1.37	3.42 ± 2.19	9
Group 6	3.14 ± 2.02	1.29 ± 1.91	4
Group 7	2.84 ± 1.63	3.59 ± 1.57	4
Group 8	2.74 ± 2.39	2.39 ± 1.25	9
	The West African Region (2002 to 2016)		
Dakar 2	1.64 ± 0.98	3.51 ± 1.32	4

Please note, the best optimal distance to the coast was 4 km, based on the lowest SLA noise and the SE from the Altimetry trends.