

# River level monitoring based on multi-mission altimetry and spatiotemporal kriging – a case study in the Mekong river basin

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### **Motivation**

Measurements of water level variations of inland water bodies by satellite altimetry got well established in the last years. For lakes and reservoirs it is possible to combine different missions and passes to one estimated water level time series with improved temporal resolution. However, it is still challenging to combine different altimeter missions and passes over rivers. We combine multi-mission altimetry data over the Mekong River using the geostatistical prediction method of ordinary spatio-temporal kriging based on empirical covariances between the altimetry observations. This way, we are able to get time series of water levels with a five day resolution at any point of the river.

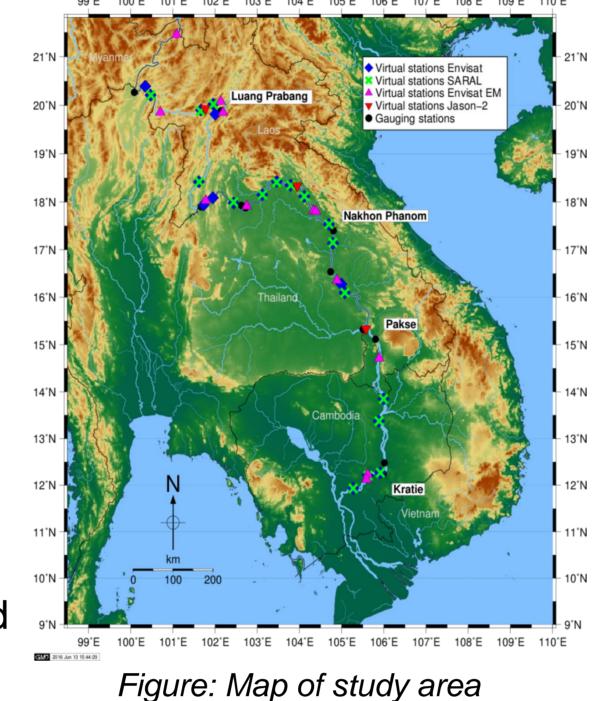
# **Data**

# Altimetry Data:

- Envisat 2002-2010
- Envisat EM 2010-2011
- Jason-2 2008-today
- SARAL/AltiKa 2013-today
- Time series are processed using the DAHITI approach [4] and applying a hooking correction [2]

### In-Situ Data:

Gauge data until end of 2012 are provided by the Mekong River Commission (MRC).



Method

#### Spatio-Temporal Ordinary Kriging along Rivers

- Kriging is an interpolation method governed by spatial and temporal dependencies between the observations [3].
- Spatio-temporal ordinary kriging is an extension to spatial ordinary kriging.
- The predicted values are a weighted sum of all observations  $Z(x_1)...Z(x_n)$

with 
$$p(Z(\boldsymbol{x}_0)) = \sum_{i=1}^n \lambda_i Z(\boldsymbol{x}_i), \quad \text{where} \quad \sum_{i=1}^n \lambda_i = 1$$
 
$$\boldsymbol{\lambda} = (\boldsymbol{c} + \mathbf{1} \frac{(1 - \mathbf{1}^\top \boldsymbol{\Sigma}^{-1} \boldsymbol{c})}{\mathbf{1}^\top \boldsymbol{\Sigma}^{-1} \mathbf{1}})^\top \boldsymbol{\Sigma}^{-1} \quad \text{with the covariances}$$

$$\boldsymbol{c} = (C(\boldsymbol{x}_0, \boldsymbol{x}_1), \dots, C(\boldsymbol{x}_0, \boldsymbol{x}_n))^{\top} \text{ and } \Sigma = (C(\boldsymbol{x}_i, \boldsymbol{x}_j))_{i,j=1...n}$$

# Covariance Models

- The spatio-temporal covariance C needed in kriging is modelled with two different covariance models. The models are based on the empirical covariance of the altimeter measurements.
- The spatio-temporal covariance is modelled by a product of the spatial and the temporal covariance

$$C_{st}(h_s, h_t) = C_s(h_s)C_t(h_t)$$

# Stationary Covariance Model

- This models assume stationarity along the river in the whole study area.
- The temporal covariance is modelled with an exponential covariance model with nugget (discontinuity around zero) and the spatial covariance is modelled with a linear tent covariance model with nugget.

# Non-Stationary Covariance Model

- The temporal component is modeled as in the stationary covariance model
- The spatial non-stationary component consists of two parts

$$C_{\mathcal{S}}(s_1, s_2) = \pi_{\text{riv}} C_{\text{riv}}(s_1, s_2) + \pi_{\text{euc}} C_{\text{euc}}(s_1, s_2),$$

- River part, based on the upstream model by Ver Hoef et al (2006) [5]
- Euclidean Part based on distance between hydrological locations of the sub-catchements.

More details on the method can be found in [1]

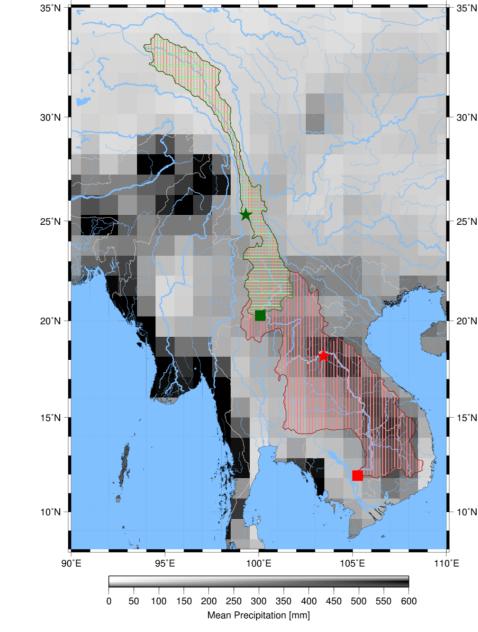
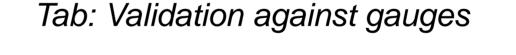


Figure: Two exemplary hydrological locations

## **Results & Validation**

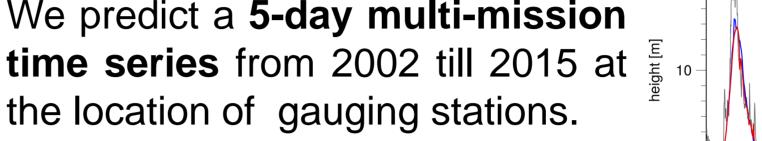
- We predict a **5-day multi-mission** the location of gauging stations.
- The results are validated against
- Prabang, Nakhon Phanom, Pakse, and Kratie, the validation is shown in detail below.
- Comparison is done with the simplest prediction, i.e., a mean annual signal

Luang Prabang 1.02 0.91 0.91   Nakhon Phanom 0.82 0.94 0.94   Pakse 0.92 0.92 0.92   Kratie 1.29 0.92 0.92   Non-Stationary Covariance Model   Luang Prabang 1.11 0.89 0.91   Nakhon Phanom 0.89 0.93 0.94   Pakse 0.88 0.93 0.93   Kratie 1.15 0.94 0.94   Annual Signal					
Pakse 0.92 0.92 0.92 0.92   Kratie 1.29 0.92 0.92   Non-Stationary Covariance Model   Luang Prabang 1.11 0.89 0.91   Nakhon Phanom 0.89 0.93 0.94   Pakse 0.88 0.93 0.93   Kratie 1.15 0.94 0.94					
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Non-Stationary Covariance Model     Luang Prabang   1.11   0.89   0.91     Nakhon Phanom   0.89   0.93   0.94     Pakse   0.88   0.93   0.93     Kratie   1.15   0.94   0.94					
Luang Prabang1.110.890.91Nakhon Phanom0.890.930.94Pakse0.880.930.93Kratie1.150.940.94					
Nakhon Phanom 0.89 0.93 0.94   Pakse 0.88 0.93 0.93   Kratie 1.15 0.94 0.94					
Pakse 0.88 0.93 0.93   Kratie 1.15 0.94 0.94					
Kratie 1.15 0.94 0.94					
Annual Signal					
Annual Signal					
Luang Prabang 1.50 0.81 0.83					
Nakhon Phanom 1.25 0.85 0.86					
Pakse 1.20 0.86 0.87					
Kratie 1.69 0.87 0.88					



Influence of Available Altimeter Data





in-situ gauging stations. For four gauging stations, Luang

RMS [m] R<sup>2</sup>

NSE

<b>,</b>	height [m]	10 —		
1		5		
		0 200	06 2007 2	800
		20		+
		15 —		- - - -
	height [m]	10 -		
		5		<b>\</b>
		0 201	0 2011 2012 2013 2	014
			- Product Covariance - Non-Stationary Covariance - Gauge	

Figure: Time series at the gauging station Luang Prabang

- The two covariance models result in similar time series
- The results with the non-stationary model show more short term variations

To check, if the available altimeter input data sets have an influence on the prediction results, we compute an RMS of a moving 1-year window for all gauges.

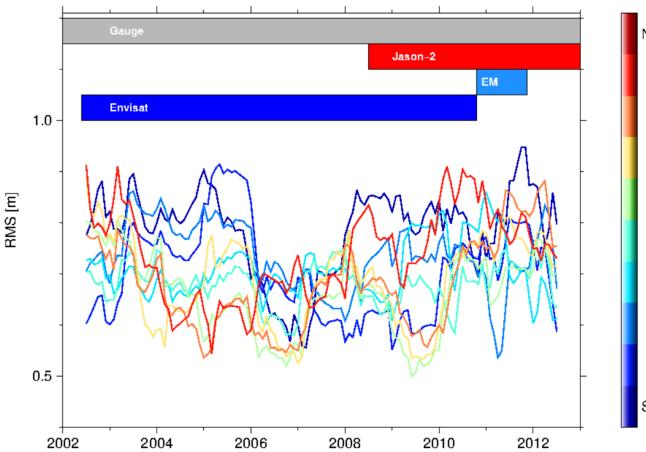


Figure: Yearly RMS values at 9 gauging stations

(color coded according to location)

- The prediction quality changes interannualy.
- The variation of the annual RMS of one station is larger than the differences between the stations.
- No deterioration is visible in the results after the end of the Envisat mission in 2011.
- No improvement with the launch of Jason-2 in 2008 is visible.

# Conclusion

- The kriging method is able to link water heights from multi-mission altimetry along the Mekong River.
- Resulting river level time series have a high temporal resolution of 5 days (adaptable).
- The two covariance models yield similar results, but the non-stationary model is able to incorporate tributaries.
- The years of data gap between Envisat and SARAL are well predicted even if only three time series of Jason-2 are available.
- Outlook: Implementation of Cryosat-2 (long-repeat orbit, dense ground track pattern) will further improve the resolution of water level estimates.

# References

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