Technical University of Denmark

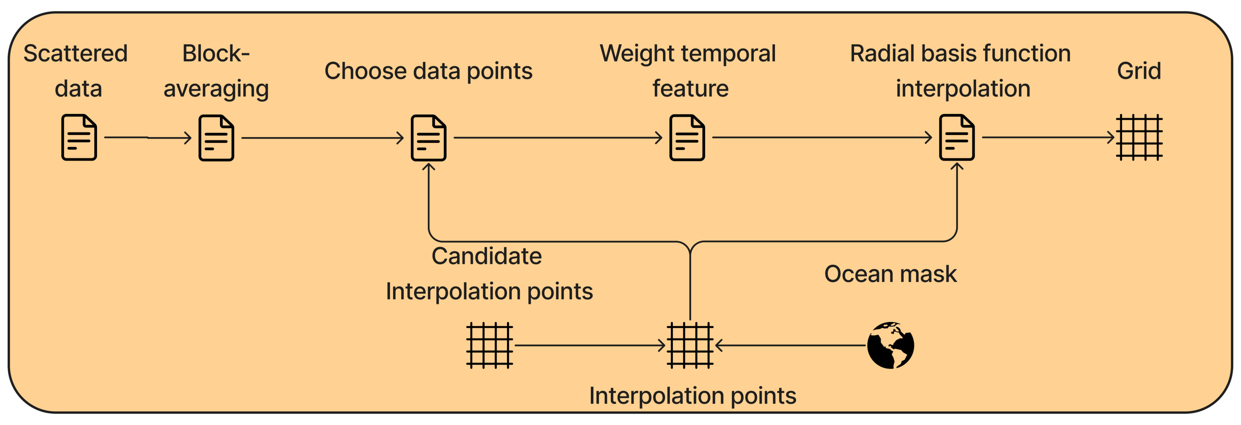
A NEAR-GLOBAL IMPROVED GRIDDED MULTI-MISSION DAILY SLA PRODUCT SLIGHTLY BEYOND REAL-TIME

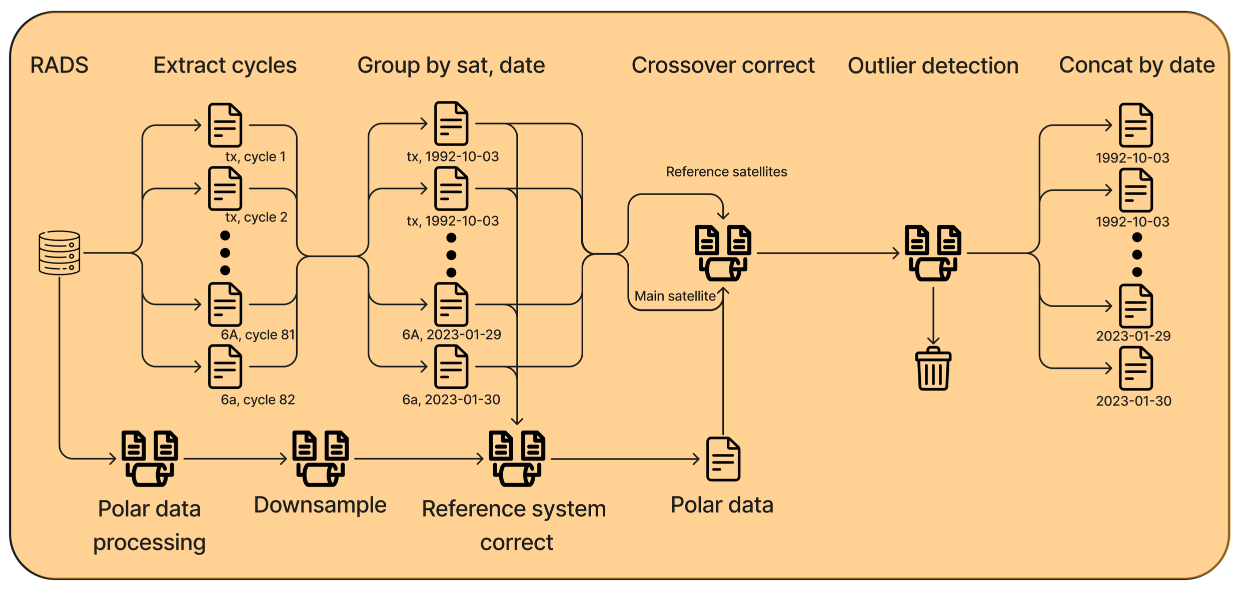
Mathias Jensen (DTU Space, mathias171292@live.dk Casper Bang-Hansen (DTU Space, Denmark); **Ole Baltazar Andersen** (DTU Space, Denmark, oa@space.dtu.dk); **Carsten Ludwigsen** (DTU space, Denmark); **Mads Ehrhorn** (DTU Fotonics, Denmark)

Abstract

In order to cover data gaps and mitigate data errors in gridded satellite altimetry both MEaSURES and CMEMSa global products are created using large temporal windows during interpolation, as well as spatial and temporal filtering. In this presentation we present a new product from the Technical University of Denmark (DTU) being a new global ¼ º x ¼ º SLA grid product containing more well-resolved features in time. Compared to related SLA data products from CMEMS and MEaSUREs, the SLA grid created in this project performs similarly. The DTU products is updated daily with less than 24 hours latency.
As an alternative to traditional filtering methods, an autoencoder is applied to the data after gridding to create a smart filter for removing satellite tracks and non-physical noise. Preliminary results are propitious, as satellite tracks are successfully removed from the data without influencing the major underlying features. The size of the latent space in the autoencoder directly determines the amount of information propagated through the filter.

Finally, the data product is used to forecast near-future values of the SLA grid using an Encoder-Decoder Attention Convolutional Long Short-Term Memory (EDAConvLSTM) architecture to close the publishing gap created by the moving temporal window in the gridding process. The prediction power of the model is very dependent on the smoothness of the data. For the SLA grid product produced in this report, however, the forecast may be used to extend the grid product slightly beyond real-time, such that a few future days are included.





Specifications	CMEMS	MEaSUREs	CMDTU
Spatial resolution	1/4 x 1/4	1/6 x 1/6	1/4 x 1/4
Temporal resolution	1 day	5 days	1 day
Latitude extent	+/- 80	+/- 80	+/- 88
Spatial distance function	Euclidean	Euclidean	Haversine
Temporal window for interpolation	6 weeks	30 days	5 days
Interpolation method	Kriging	Kriging	Radial Basis Functions

Polar data

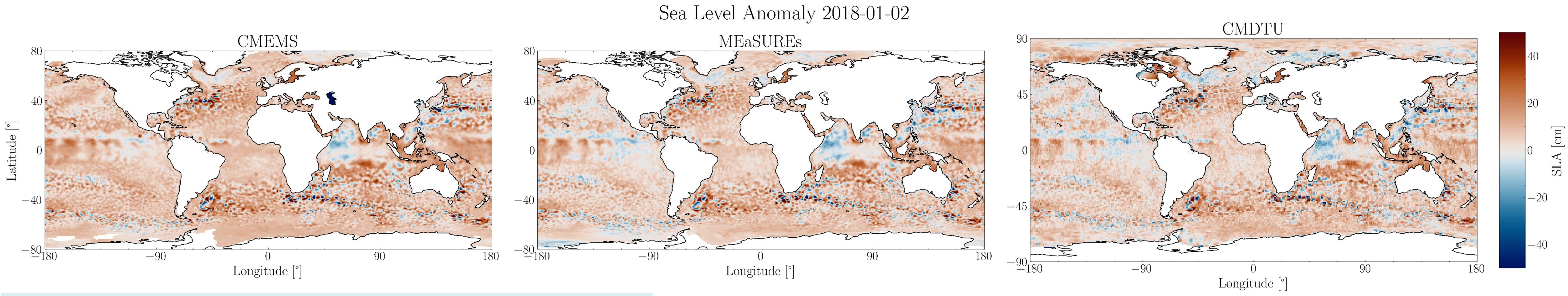
To expand the reach of the data product to the polar regions, data from these regions have been re-processed for the entire 30-year period using the data by Rose et al. 2019.
For the ERS/Envisat period, sea level information to the 82⁰ has been provided using the Ales+ retracker. Since 2010 Cryosat-2 provided sea level information to 88⁰N using the SAMOSA+ physical retracker.

Haversine Distance

Other similar products interpolate assuming a Euclidean distance between data points. However, on the near-spherical earth the haversine distance metric is a much better approximation. The haversine, or great circle distance is given by:

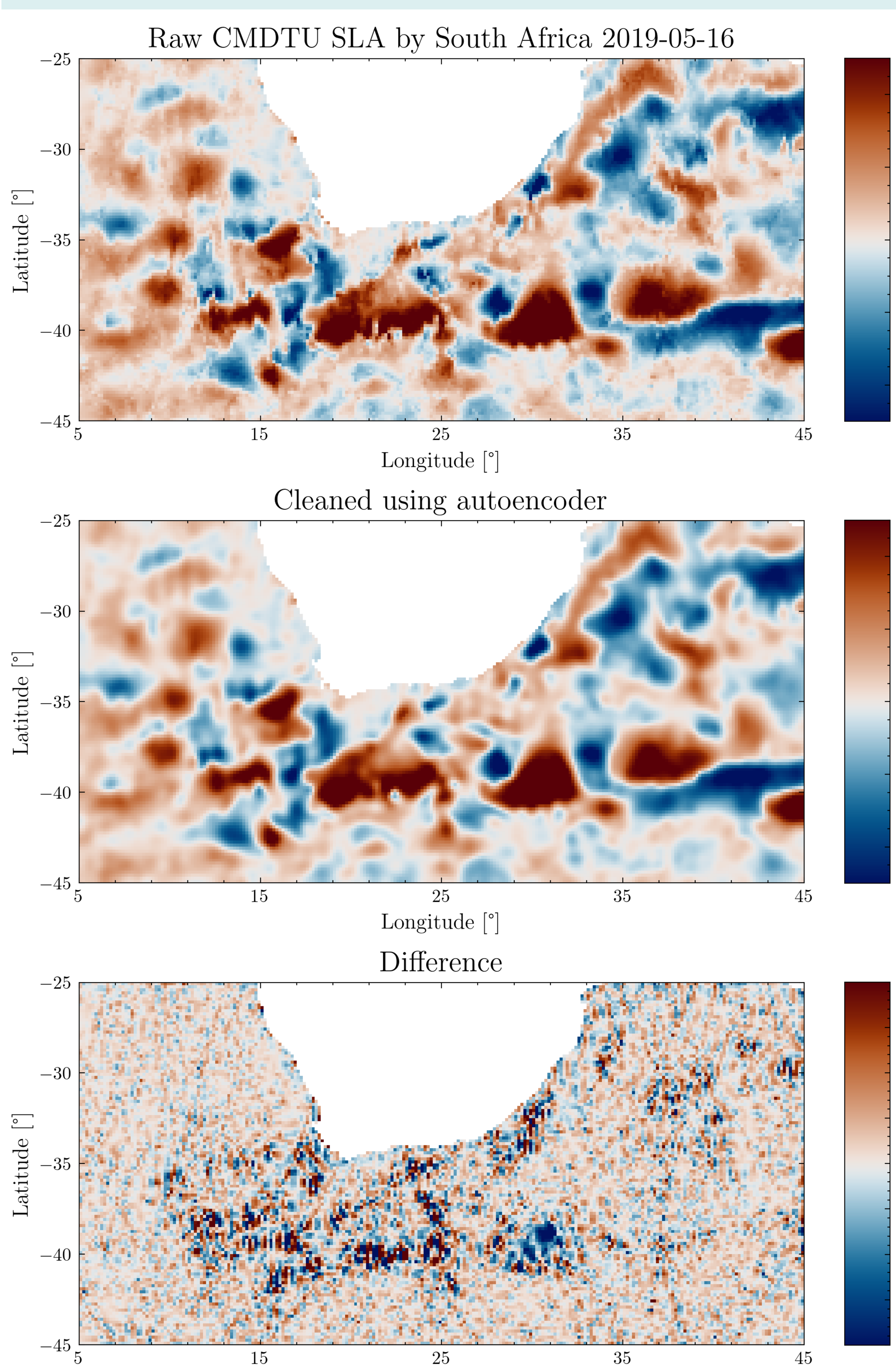
$$Haversine(\phi_1, \lambda_1, \phi_2, \lambda_2) = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)$$

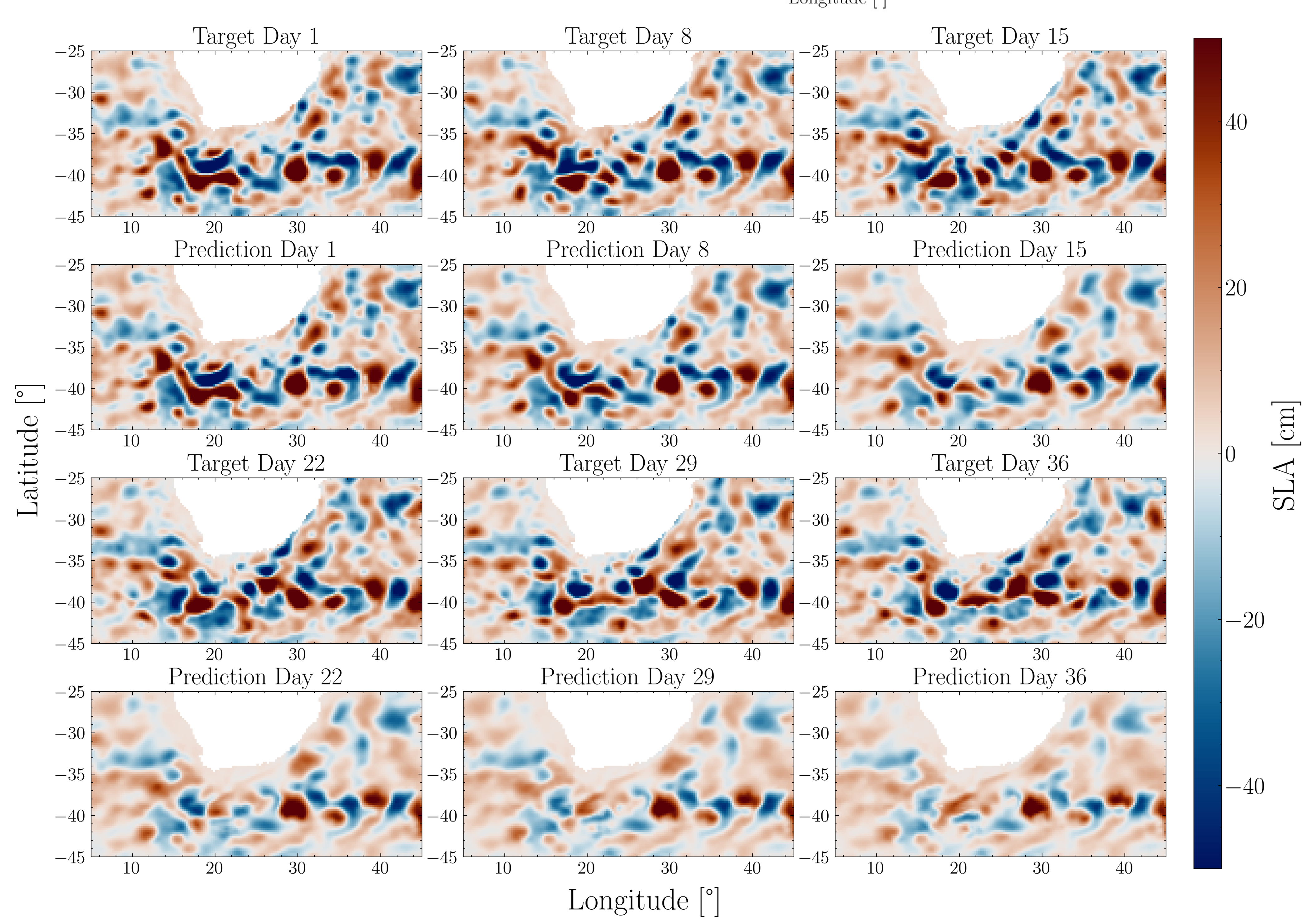
Sea Level Anomaly 2018-01-02

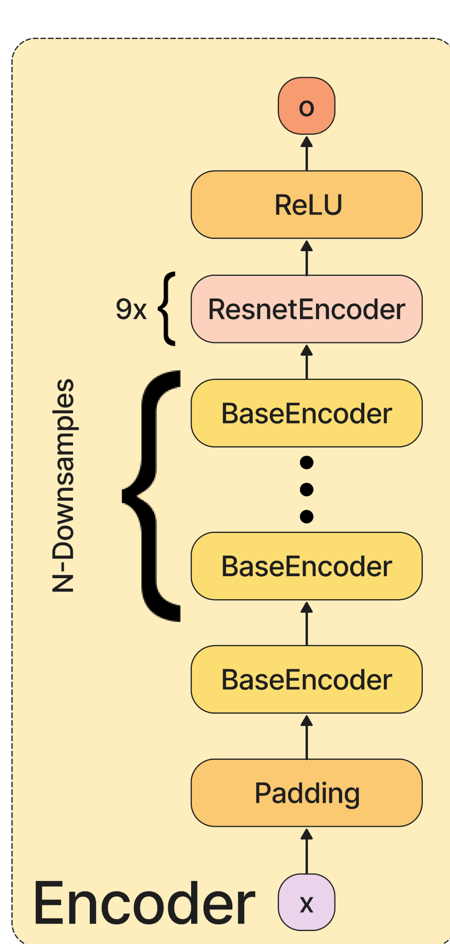


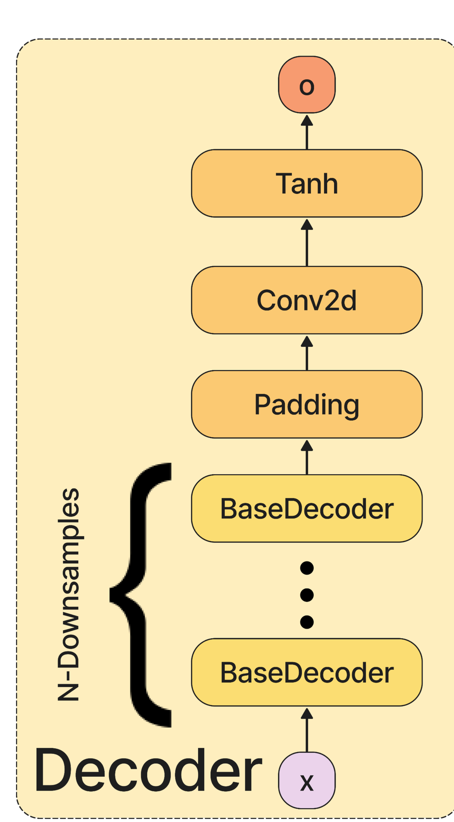
Autoencoder for noise removal

In producing the grid SLA product, no filtering of the original data is applied. Only corrections such that the data are all relative to the same reference. Thus, the resulting product is more error prone than CMEMS or MEaSUREs, which both use heavy filtering of the data. Therefore, to subsequently remove non-physical noise from the data product an autoencoder architecture has been utilized. First, the data are passed through the encoder-decoder, which learns the general features. Then, the autoencoder-output is produced, which may be treated as a cleaned version of the data. The level of noise removal may be adjusted by the size of the latent space in the autoencoder









Forecasting using neural networks

SLA data products are created using a moving temporal window of data to use in the grid interpolation. Hence, the published data is behind by at least the size of this window. To reduce this delay, an encoder-decoder ConvLSTM with attention neural network architecture is used for forecasting near future sea level anomalies. Additionally, the process is speeded up by employing the latent space from the autoencoder architecture used for removing noise to reduce the data dimensionality.

References

Rose, Stine K., Andersen, . B. ; Passaro, M Ludwigsen, C. B. ; Schwatke, C. (2019) Arctic Ocean Sea Level Record from the Complete Radar Altimetry Era: 1991-2018, Remote Sensing 11, Issue 14, pp. 1672