Chlorophyll-a satellite images inpainting

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Introduction

On-board satellite imagers provide key geophysical parameters (temperature, chlorophyll-a, ...) at a global and daily scale. These observations are sparse mainly due to missing data caused by cloud coverage and orbital characteristics (e.g. Fig 1)

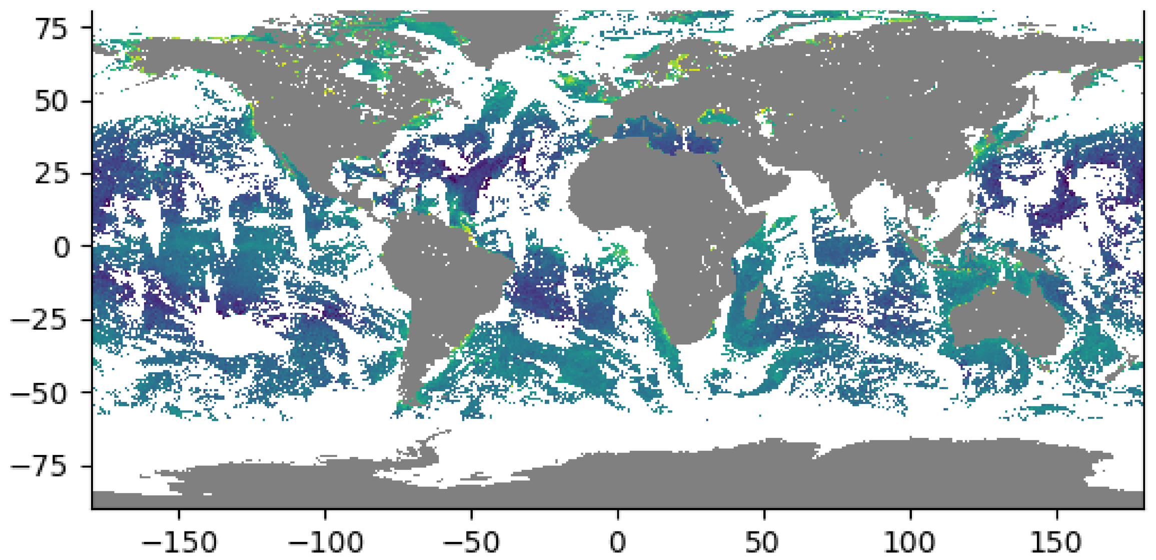

Figure 1: Chlorophyll-a concentration provided by GlobColour on 02 August 2008.

Objective

The objective of this work is to propose two algorithms to complete missing satellite data (inpainting) and evaluate them through a twin experiment.

Data

31452 data were selected from Globcolour daily images from 1997 to 2014:

- Regions selected in west Med Sea (64 × 64 pixels images) between 36-40^{o}N and 1-10^{o}E (e.g. Fig. 2)
- Images with more than 90 % of valid pixels were kept
- Artificial cloud masks were randomly added. (e.g. Fig. 3)

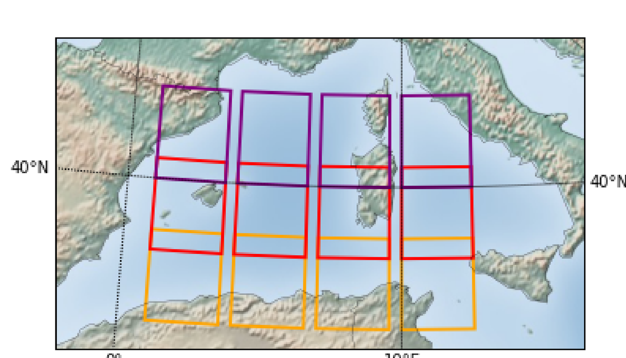

Figure 2: Areas in West Mediterranean Sea selected for the study

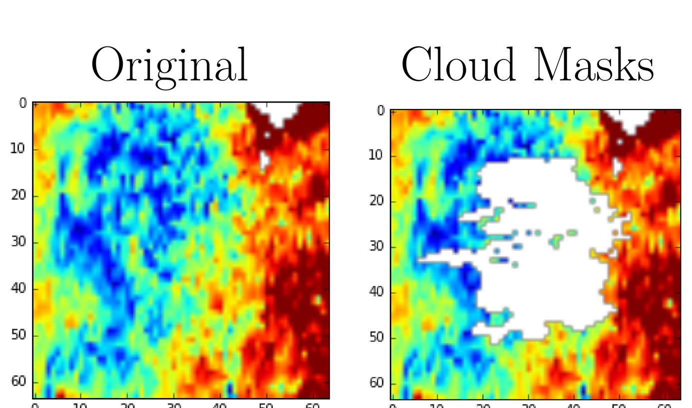

Figure 3: Example of generated masks

Description of the algorithms

Kriging

The Krigging method aims at providing a best estimation of the chlorophylle-a's field at unknown points using spatial correlation. Here we used ordinary Krigging assuming a constant unknown mean and no trend in our data. The method is a linear combination of observations weighted by correlations between the observations and the prediction point. The correlation is characterized by a semi-variogram, which quantifies covariance between points for a specific distance.

Context Encoder

The Deep-Learning method is based on a neural Context Encoder. The network is composed of an encoder and a decoder both with 4 convolution layers.
The network was trained using 10620 images for 50 epochs.The loss function is evaluated using a L2 norm on an expanded mask with weights (0.1 in the center, 1 on the edges) over the missing values in order to emphasize the consistency of the prediction with the context.

Output of the proposed algorithm

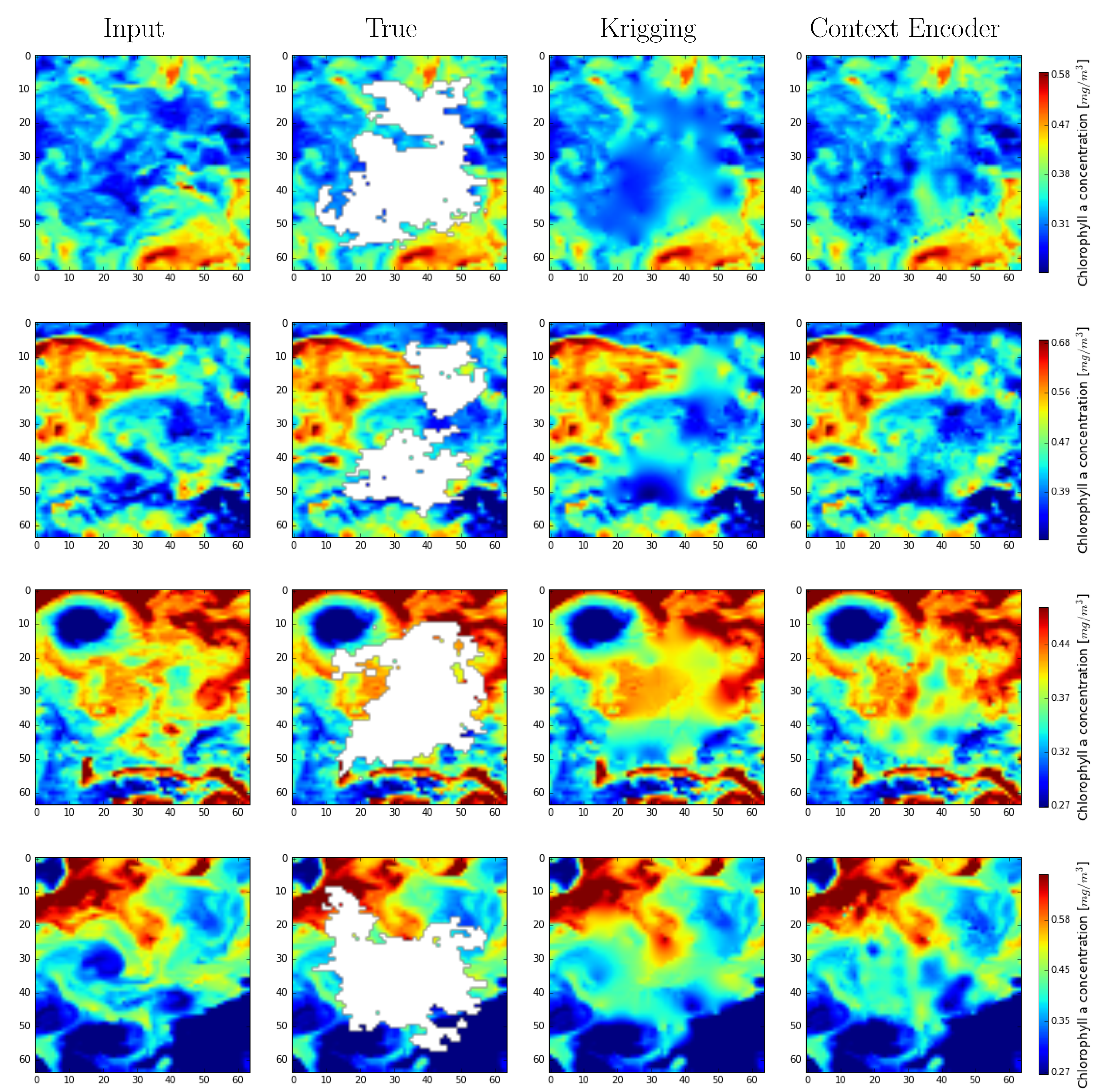

Figure 4: Examples of reconstructions using Krigging and Context Encoder

Performances

The performances are measured using the Root-Mean Square Error (RMSE), the coefficient of determination (R^2) and the Spatial Variance Ratio (SVR, calculated for each image) between the prediction and the real image. The SVR is used as an indicator for the preservation of the chlorophyll-a spatial distribution. They are presented in Fig. 5.

	RMSE	R^2	SVR (median)
Context Encoder	$3.67 \cdot 10^{-3}$	0.81	0.78
Krigging	$2.79 \cdot 10^{-3}$	0.86	0.65

Figure 5: Comparative table of Context Encoder and Krigging performances over the 100 images of the validation dataset

The Boxplot (e.g. Fig. 6) reveals that the reconstruction achieved by the Context Encoder has the best retrieval of the spatial dynamic of the chlorophyll-a.

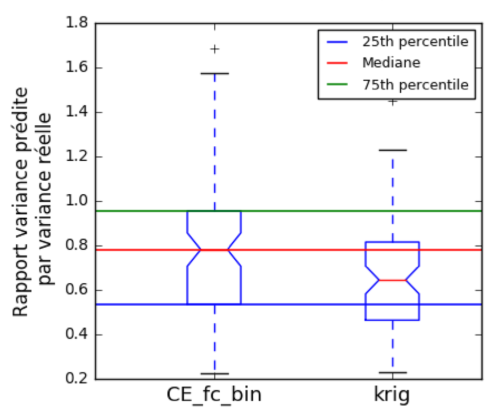

Figure 6: Boxplot of spatial variance ratio for Context Encoder and Krigging

Conclusion

This work compared two inpainting methods: an interpolation technique, Krigging, and a neural network, the Context Encoder. The results suggest that the Context Encoder is as good as an statistical optimal interpolation to reconstruct chlorophyll-a structures under clouds. When reconstructing smaller structures, the Context Encoder seems slightly better.
This work will continued focusing on :

- Adding temporal inputs to improve the reconstruction for all methods
- Testing a Generative Adversarial Networks (GAN) architecture

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