# Unsupervised classification of altimetric waveform over all surface type


**Arnaud QUESNEY, Eric JEANSOU, Christian RUIZ**

*NOVELTIS, 2 avenue de l'Europe, Ramonville-St-Agne, France*

**Nathalie STEUNOU, Bruno CUGNY, Nicolas PICOT, Jean-Claude SOUYRIS**

*CNES, 18 avenue Edouard Belin, Toulouse, France*

**Sylvie THIRIA, Mustapha LEBBAH**

*LOCEAN/IPSL, 4 place Jussieu, Paris, France*

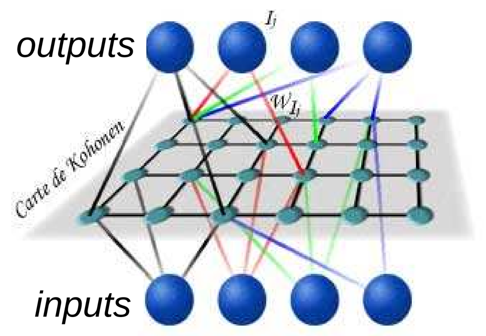
Contact : M. Arnaud Quesney
arnaud.quesney@noveltis.fr



## Summary

We have developed a method for the automatic identification of the surface type from a sample of altimetric waveforms. It is a preliminary stage to the treatment of the waveforms specific to each surface type which provides an adequate algorithm able to extract relevant geophysical information.
NOVELTIS has implemented a waveform unsupervised classification scheme using a neuronal approach founded on the self-organizing topological maps (Kohonen approach). The interest of such a method is that it is fast, powerful and that it makes it possible to process information mixing quantitative and qualitative data.
The performances of the classifier are performed through a comparison with expert fields produced by CNES. The results have shown that the classes are labeled with more than 88% success for the Ocean, Land Surface, Sea Ice and Coasts types.
We have applied the learned classifier to a Jason-1 cycle. The results obtained have underlined the robustness of the neuronal waveform classification. The interpreted classes present good space-time coherence. Sea ice space covers can, for example, be clearly delimited. A first validation of the sea ice extension has been carried out using the products deduced from SSM/I data. Lastly, we have shown that neuronal classification made it possible to very finely identify the continental ice surface type.


## Methodology

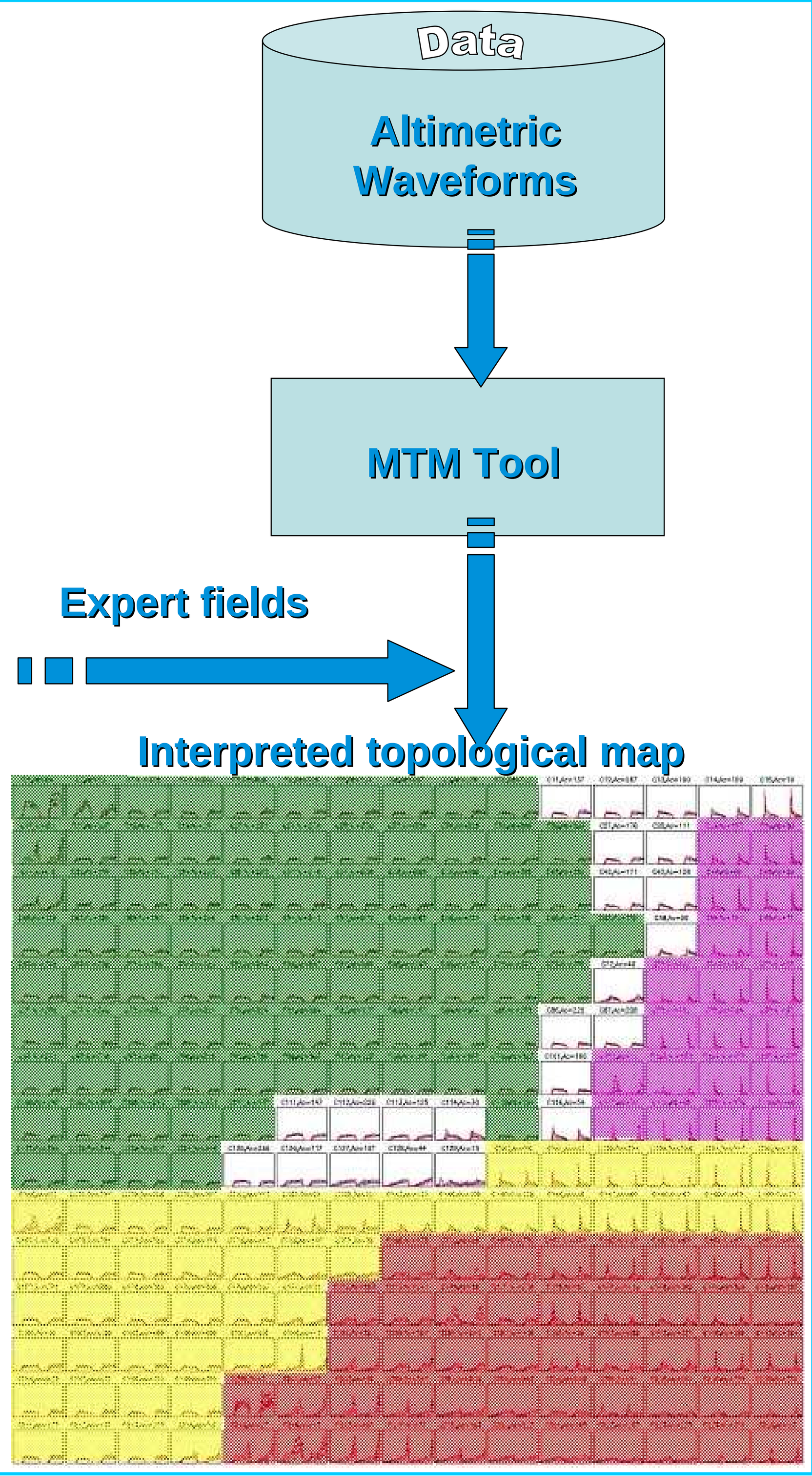



We have applied an automatical classification of altimetric waveforms using a **neuronal approach** founded on the **self-organizing topological maps** (**Kohonen** approach). These maps belong to a family model with "unsupervised learning process" that lead to the gathering of similar data.

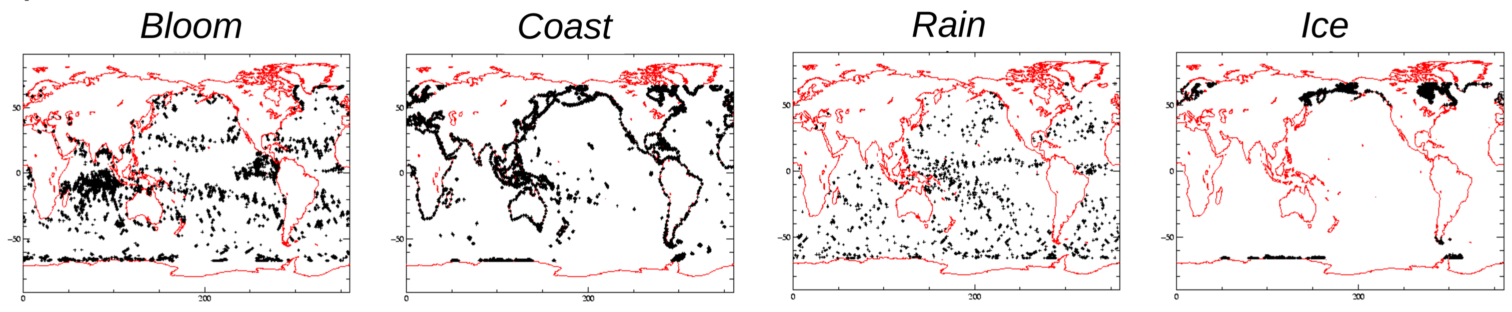
The **unsupervised classification** method used in this study is dedicated to quantitative and qualitative data. The input vector is composed of **Jason-1 waveforms measured in Ku and C-band associated to 2 qualitative flags** representing a sea-land mask (available in SGDR products). A learning base and test base have been created with these input vectors.
The **objective** was the classification of the following principal surfaces:

- Ocean (« Brown »),
- Ocean with rain disturbance (rainy cell),
- Specular ocean (Sigma0 Bloom),
- Sea ice,
- Coastal zones (radar echoes are disturbed by land),
- Land surfaces.

## Implementation




NOVELTIS has optimized the whole classification process (input vectors, topological map, learning process). The classification step has been achieved on the learning base data with the **MTM tool (Mixed Topological Map)** from LOCEAN/IPSL. The implemented method has been fast and efficient.
In order to validate and to obtain the classifier performance, we have validated the classifier on the test base data using **expert fields** provided by CNES.

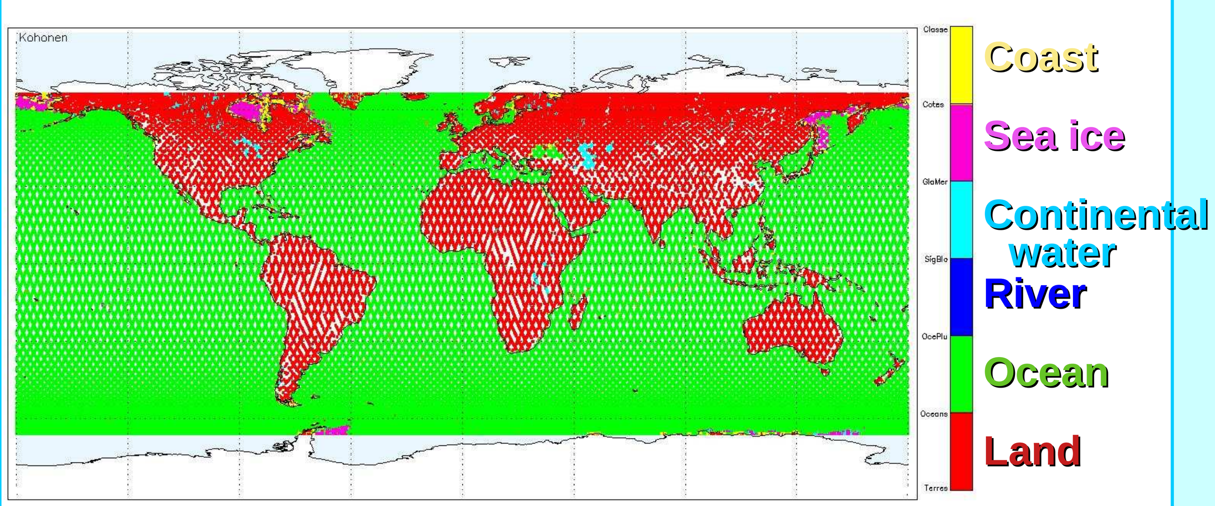



In these models, the classification result is presented as a graph called « **topological map** » where resembling categories (classes of altimetric waveform shapes) are close spatially.
The results have shown that the **classes are labeled with** more than 93% **success** for the ocean, 100% for land surfaces, 88% for sea ice and 100% for coasts types.

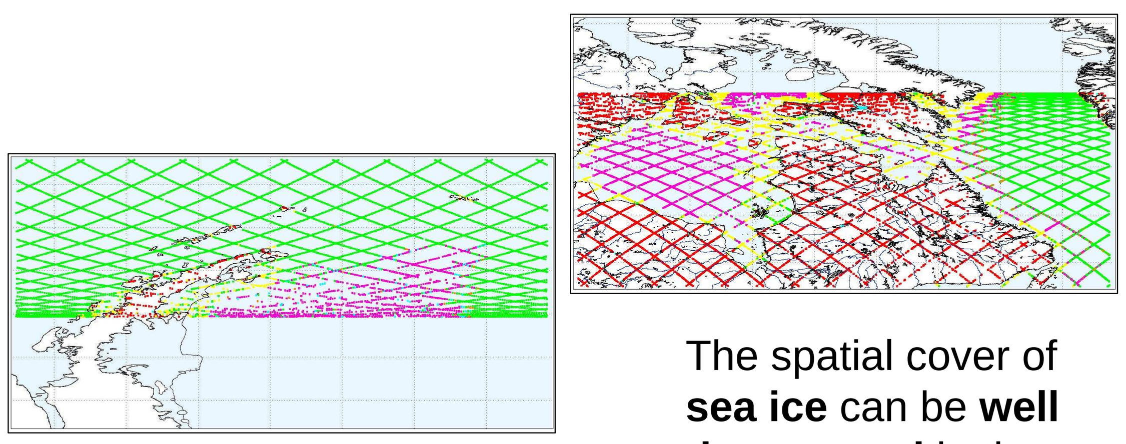
| Expert field: | Land | Ocean | Sea ice | Coastal zone |
|---|---|---|---|---|
| Land | **100.00%** | 0.00% | 0.00% | 0.00% |
| Ocean | 3.17% | **93.06%** | 0.02% | 0.00% |
| Sea ice | 2.68% | 8.74% | **88.58%** | 0.00% |
| Coastal zone | 0.00% | 0.00% | 0.00% | **100.00%** |

## Results

We have applied the learned classifier to the **Jason-1 cycle 116** (from 1 to 10th March 2005). This is the global result of the altimetric waveform classification.




The interpreted classes have a **great spatial and temporal coherence.** The result obtained have underlined the **robustness of the neuronal waveform classification to noise measurement.**



The spatial cover of **sea ice** can be **well demarcated** in the Hudson Bay and in Antarctic peninsula.

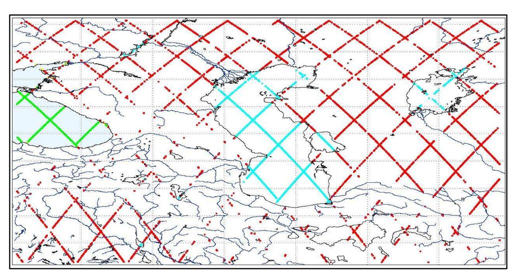
## Conclusion

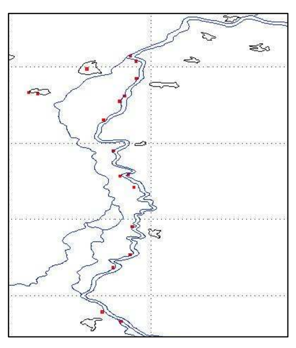
**Automatic detection of altimetric waveforms representing ocean, coast, sea ice and land surface types ⇒ Offers the possibility of applying an appropriate process for geophysical parameters estimation related to the altimetric waveform shape.**

## Intra-class variability: to an estimation of geophysical parameters

NOVELTIS has analyzed the space-time variability of classes that belong to a same type of identified surface.

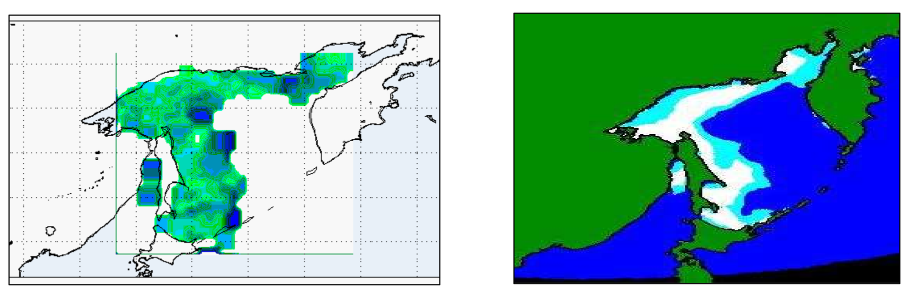
For example, continental waters are clearly detected among land surfaces.



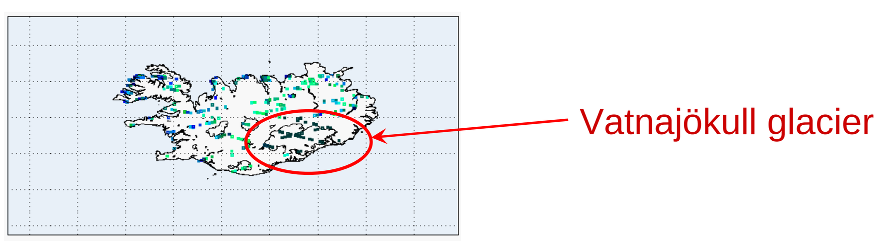


The **Ob river** in Russia is really **well detected** on the Jason-1 tracks that fly over it.

The ice covers have regular spatial variations that correspond to specific waveform characteristics.
On the figure following, the **green zones** represent **specular surfaces** while **blue zones** have **waveform less specular**, meaning they are influenced by **roughness contribution**. This result has been **validated** using the products deduced from **SSM/I data** (right figure).



Moreover, the **continental ice** can also be **automatically detected** by classification, as shown on Iceland, and could be useful to **deduce continental ice height**.




Results of classification on land surfaces are very interesting and new. The analysis of close waveforms labeled « land » has underlined **areas** that are **spatially extended**. This result is promising for the altimetric waveforms interpretation in terms of geophysical parameters. In fact, on land, altimetric waveforms could give **information about surface characteristics**. Comparison of classification of "land" waveforms and a DEM (median slope from GTOPO30) shows a high correlation in spatial structures (b-a).

Moreover, **information about volume contributions** can also be achieved. Blue zones correspond to plane areas without vegetal cover and green zones clearly represent relief or vegetal zones as it is visible on the sub-sahel band (b-c).