



# Exploring Pattern Recognition Techniques for ACSPO Clear-Sky Mask

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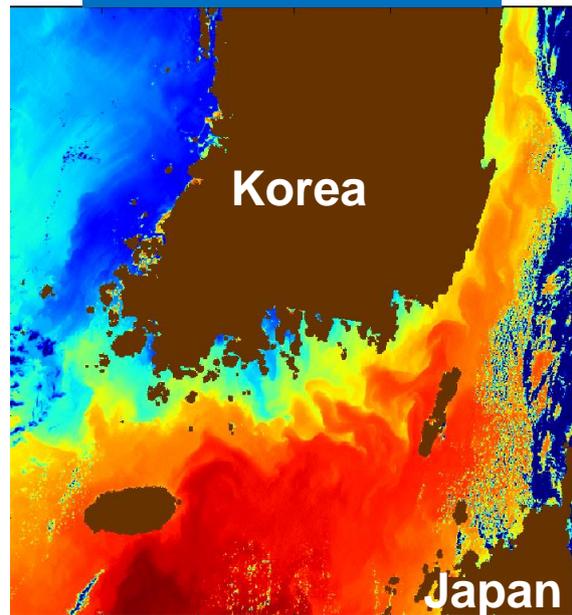
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# The Need in New Cloud Masking Approach

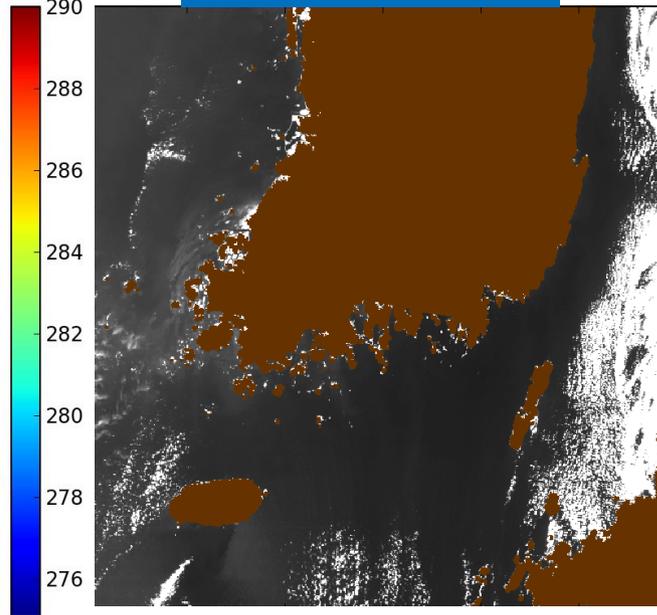
- **The current ACSM performance compares well with other world-class cloud masks.**
- **However, some cloud leakages and misdetections still take place due to incomplete discrimination between clouds and cold SST anomalies**
- **These deficiencies are best detected by visual inspection of SST – L4 images.**
- **We assume that using the pattern recognition/machine learning (ML) techniques could help improve the ACSM performance**
- **Here we present preliminary results of exploring the ML approach for cloud vs. SST discrimination.**

# Object of Analysis and Assumptions

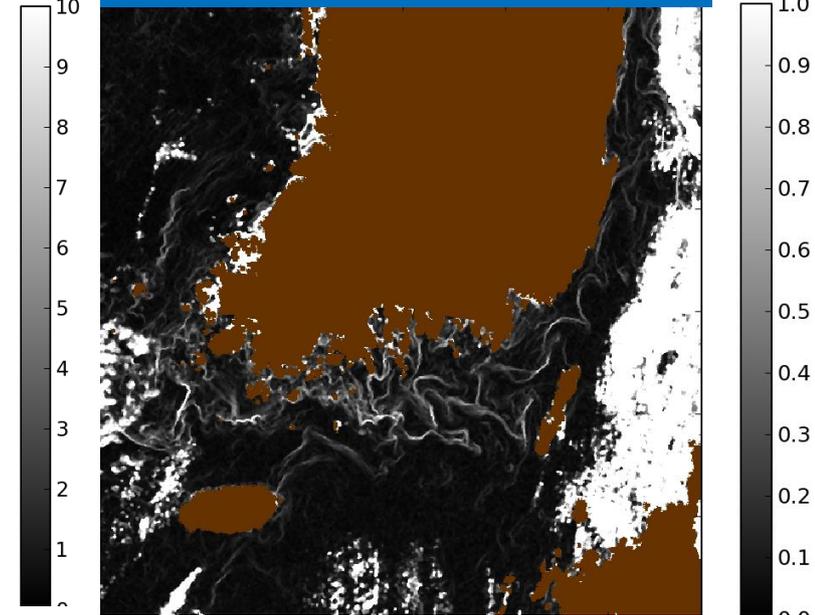
SST Regression



Ch M7 Albedo



SST Gradient Magnitude



- Analyzed images: SST retrieved from destriped VIIRS BTs (see presentation by M. Bouali) in ALL ocean pixels, both clear-sky and cloudy
- General assumptions:
  - Ocean surface is warmer and more uniform than cloud
  - Smooth, regular patterns are more typical for ocean than for cloud
  - Chaotic, highly variable structures are more typical for cloud

# The Feature Variables

The following three variables are used for classification:

1.  $T_S$  SST;

2.  $P$   $Median(M) \times Range(\cos\theta)$ ;

$$M = [(\partial T_S / \partial x)^2 + (\partial T_S / \partial y)^2]^{1/2}$$

Magnitude of SST gradient

$$\theta = \tan^{-1}[(\partial T_S / \partial x) / (\partial T_S / \partial y)]$$

Gradient angle

$$Range[\cos\theta] = Max[\cos\theta] - Min[\cos\theta]$$

Range of  $\cos\theta$

3.  $N$  Range of Wiener High Frequency SST component

$$N = \max(|T_S - S(i,j)|) - \min(|T_S - S(i,j)|),$$

$$S(i,j) = \mu(i,j) + \{[\sigma(i,j)^2 - v^2] / \sigma(i,j)^2\} [T_S(i,j) - \mu(i,j)]$$

Wiener HF component

$$\mu(i,j) \text{ and } \sigma(i,j)$$

Local mean and SD of SST

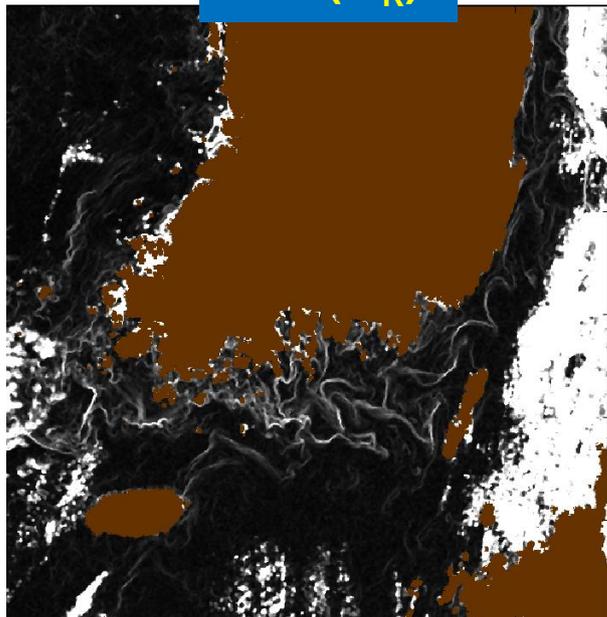
$$v^2$$

Local noise power

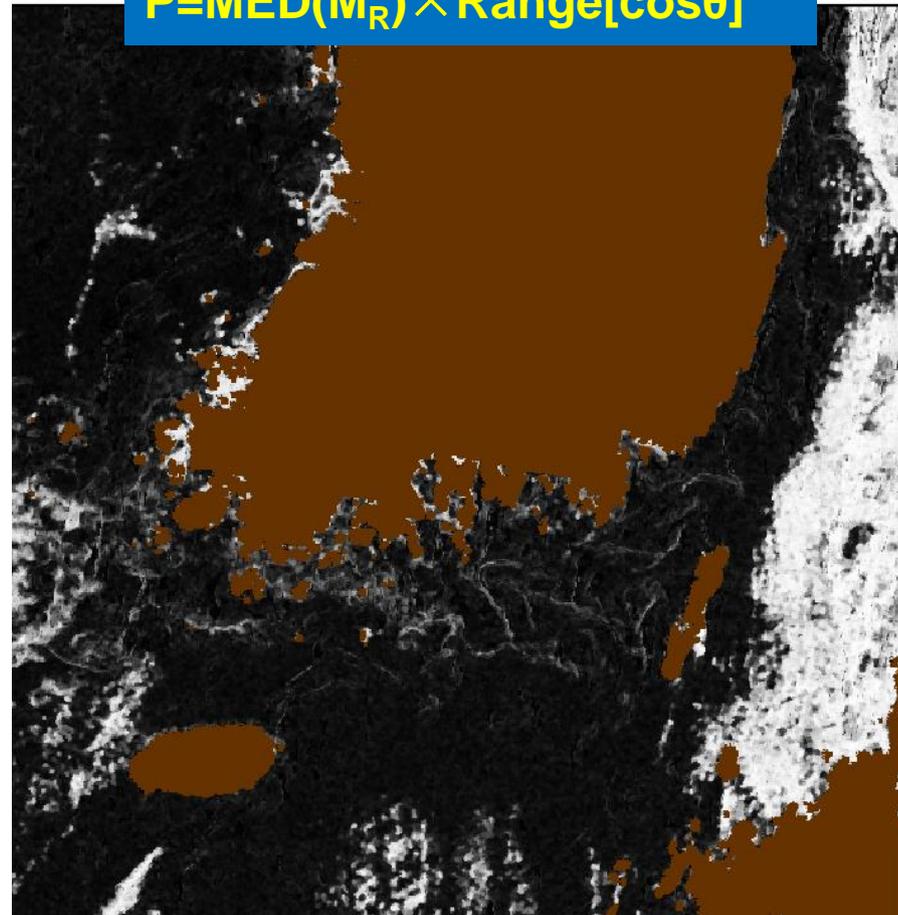
All variables except SST are calculated within  $3 \times 3$  window

$$P = \text{MED}(M_R) \times \text{Range}[\cos\theta]$$

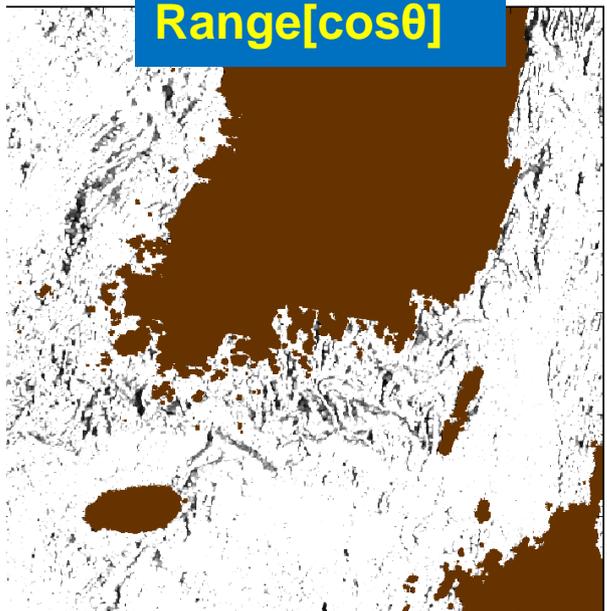
**MED( $M_R$ )**



**P=MED( $M_R$ ) $\times$ Range[ $\cos\theta$ ]**



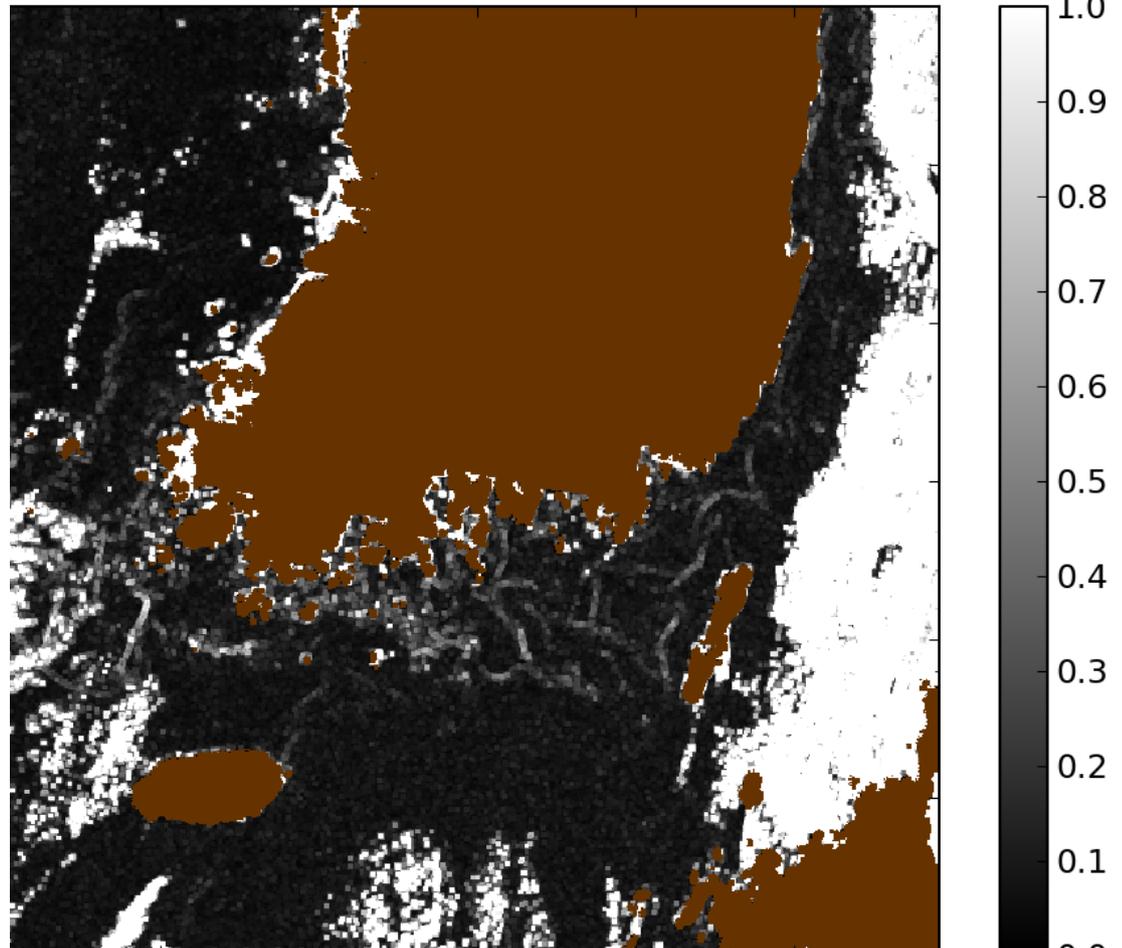
**Range[ $\cos\theta$ ]**



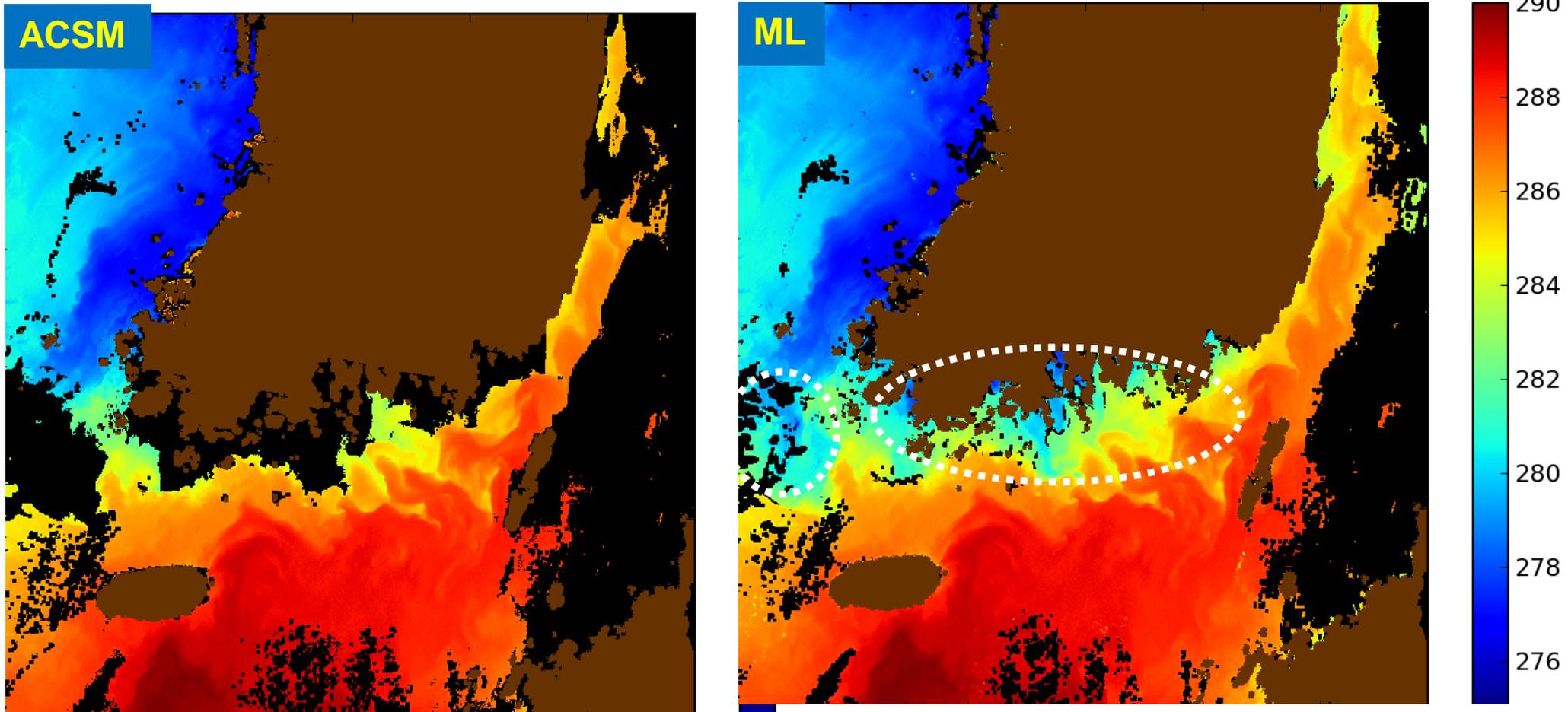
**SST fronts are suppressed in P image, but cloud is well detected**

# Range of Wiener HF Component

Variation in HF SST  
component is smaller over  
ocean and larger over cloud



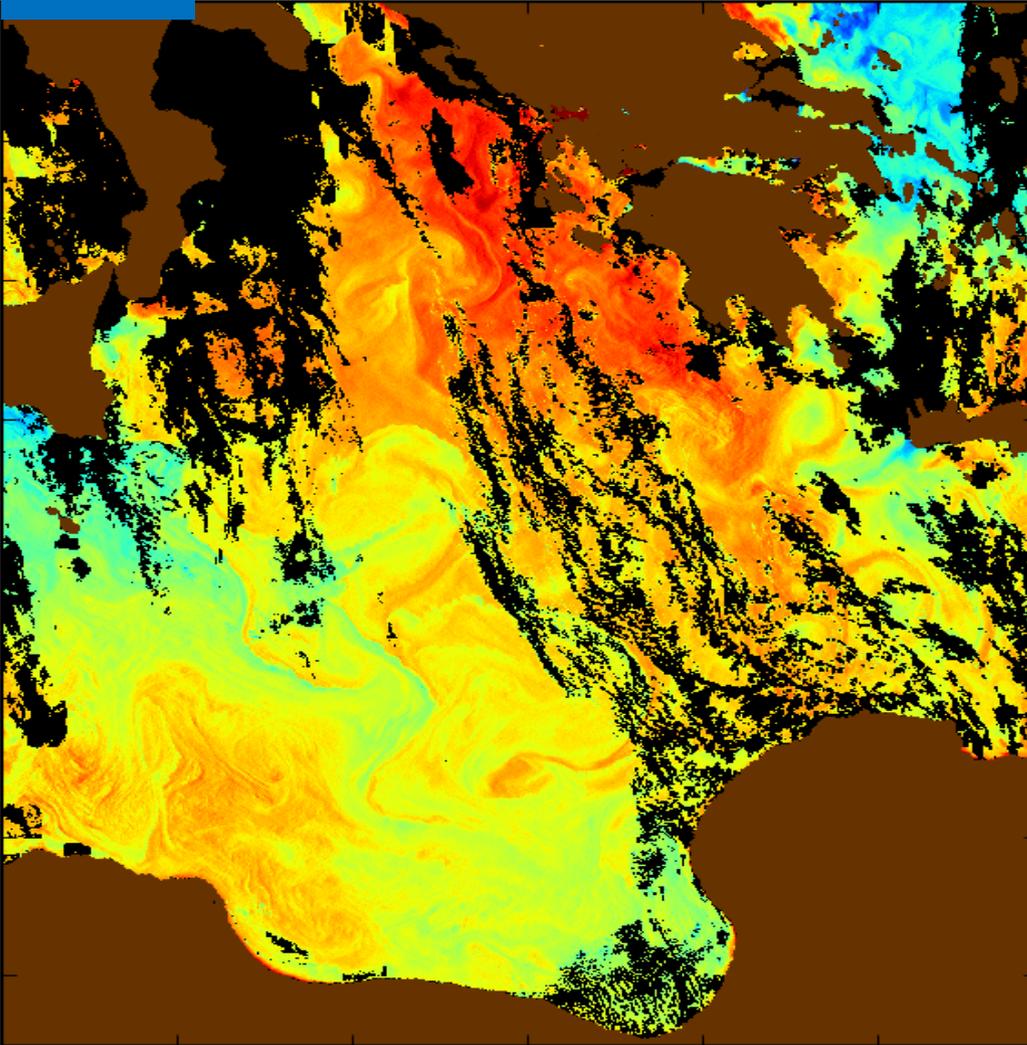
# ACSM vs ML Cloud Filter(Korea strait)



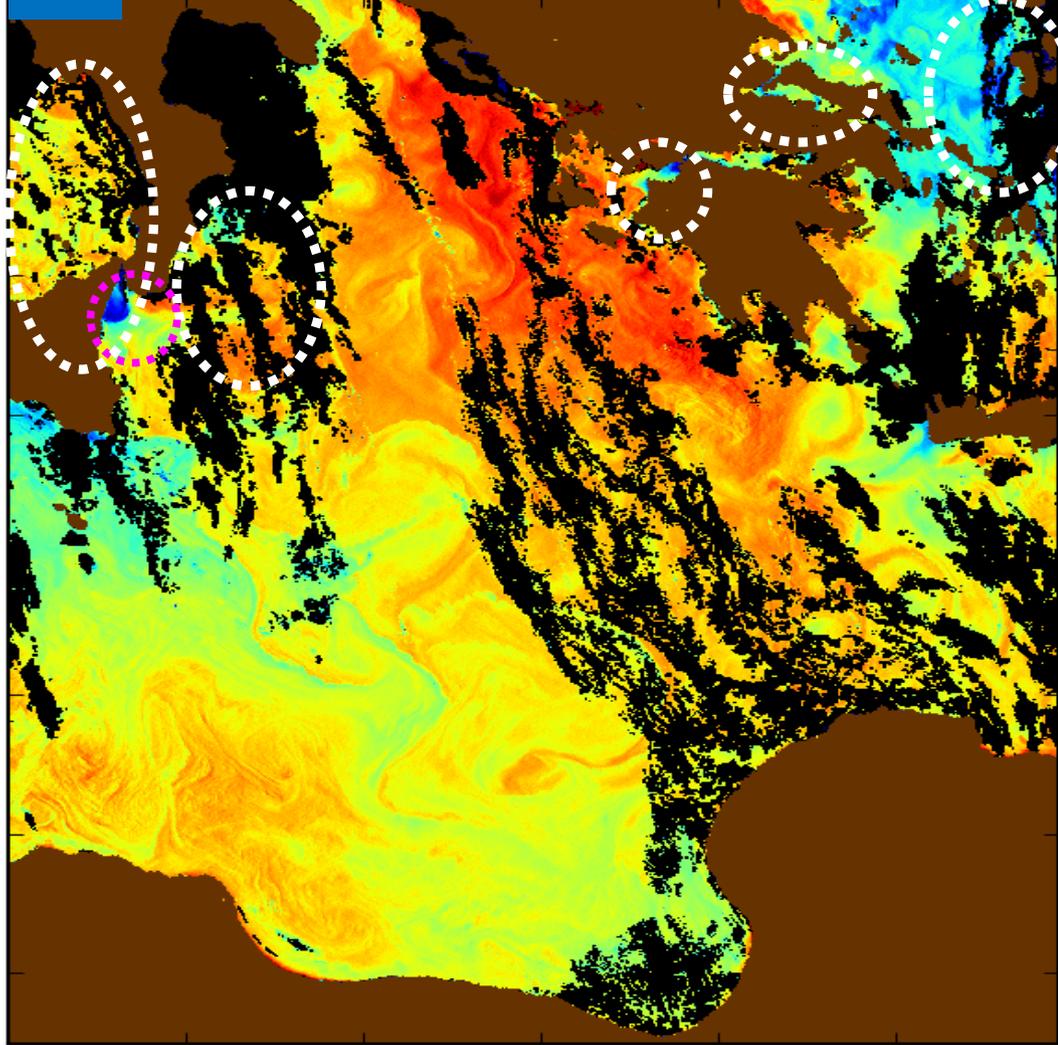
- The “Logistic Regression” algorithm was used for classification
- The ML reveals some interesting areas hidden by the ACSM, particularly in coastal zones

# ACSM vs ML (Mediterranean sea)

ACSM



ML



# Preliminary Observations

- **Pattern-Recognition/Machine Learning approach has potential to augment the current ACSPO Clear-Sky Mask**

## Future Work

- **Test the current ML approach on a representative data set of VIIRS SST (at least one full day of VIIRS data).**
- **Consider improvements to the ML algorithm, if necessary**
- **Explore using the ML algorithm as**
  - **a standalone clear-sky mask alternative to ACSM; or**
  - **an additional cloud filter within ACSM**