UNIVERSITY OF TWENTE.

REMOTE SENSING OF PRIMARY PRODUCTION IN COASTAL WATERS: THE WADDEN SEA

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IN PLACE
Primary Production Project
NWO - ZKO "Carrying Capacity" Program

ITC FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION

TALK LAYOUT

- What is IN PLACE?
- Why remote sensing?
- Challenges and requirements
- Objective
    - Cal/Val
    - Errors and spatial scale mismatch
    - primary production in coastal waters
- Preliminary conclusions

IN PLACE

Integrated Network for Production and Loss Assessment in the Coastal Environment (PI: Katja Philippart)

Team : NIOZ, IVM and ITC-UT

Objective: generate consistent measurements of pelagic and benthic primary production

Subprojects:

Monitoring network: Katja Philippart;

Algorithm automated sensors: M. van Dijk, S. Salama;

Algorithm remote sensing; J. Kromkamp, H. var der Woerd, S.Salama

Data handling and Outreach; the IT's

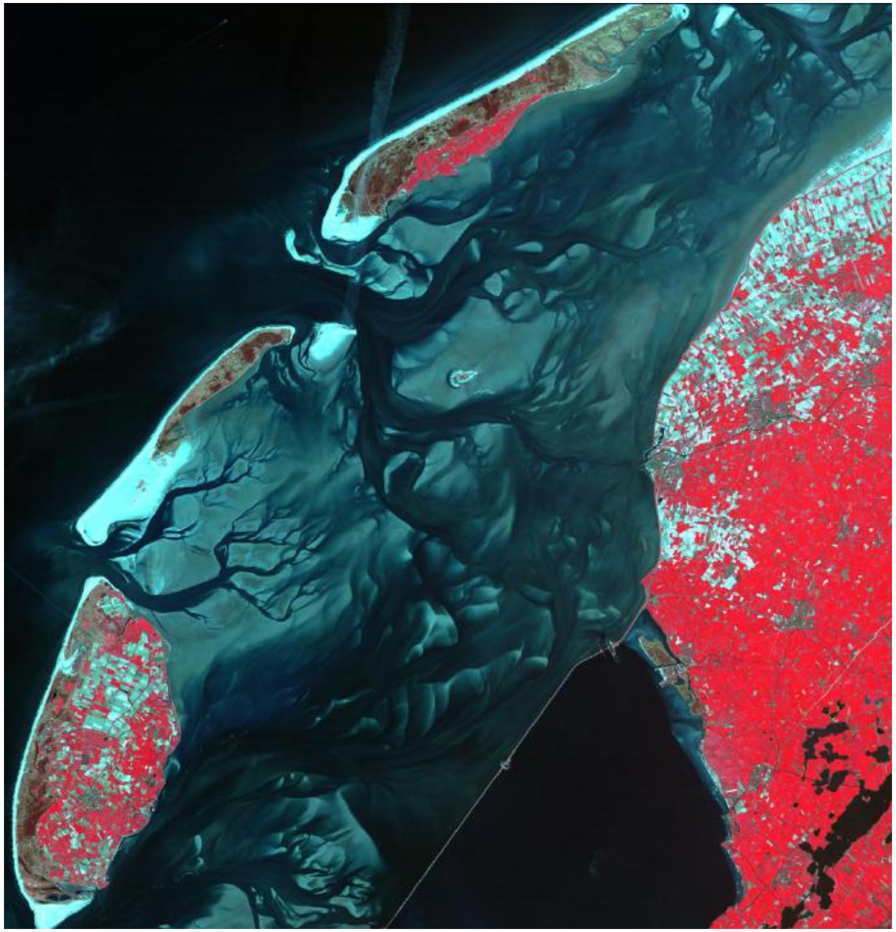
WHY REMOTE SENSING?

The abundance of phytoplankton and suspend particulate can be mapped by measuring the light coming from he sea with optical sensors carried on earth observation (EO) satellite.

It is the aquatic biosphere that is monitored uniquely by EO sensors.

EO data provides a synoptic scale and high temporal frequency of key variables:

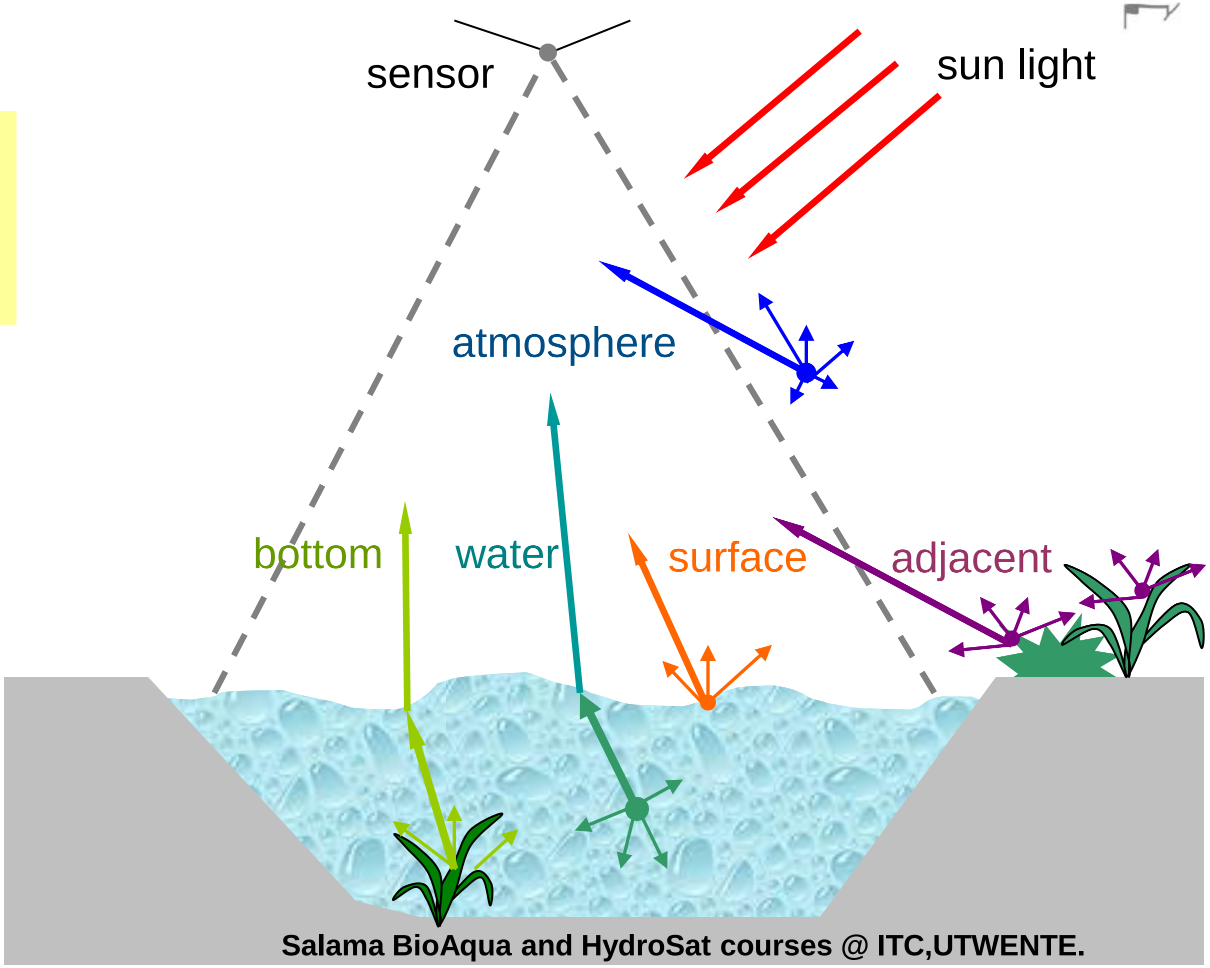
eutrophication, turbidity, SST



CHALLENGES AND REQUIREMENTS

The received light (radiance) at the sensor level is a combination of:

water +	max ~ 20 %
bottom + surface + adjacent + atmosphere	min ~ 80 %



Salama BioAqua and HydroSat courses @ ITC,UTWENTE.
Salama 2012, Treatise on Water Science, vol. 2, pp. 351–399

Working with uncertainty!
reliable corrections are required!

OBJECTIVES

Collecting intensive data set to understand primary production processes in the Wadden Sea.

To obtain consistent measurements and design reliable retrieval models we worked on:

(i) Calibrating and validating the models, the Cal/Val data set;
(ii) Estimating the uncertainty and resolving the spatial mismatch;
(iii) Enhancing the retrieval algorithm;
(iv) Investigating two NPP models, suitable for coastal water?

CALIBRATION VALIDTION DATA SET

- Form IN PLACE, PROTOOL projects we are collecting wealth of information resulting in huge data set;
- These data will be used to:
  - understand processes;
  - calibrate/validate models;
  - provide benchmark for future earth observation missions(Sentinel-3 OLCI sensor);

What is the best setup to design Cal and Val sets?

Is there an optimal manner to subdivide the collected data into Cal and Val sets such as both sets capture the actual variability of the system?

Can we estimate in-situ measurement errors?

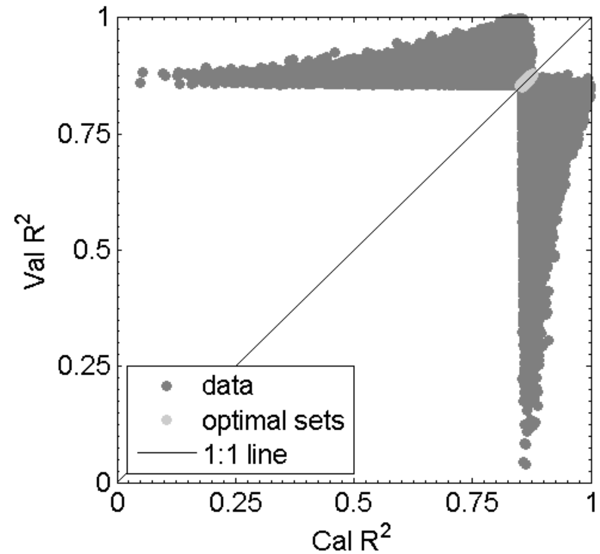
OPTIMAL CALIBRATION AND VALIDATION

GeoCalVal is a novel model that provides the:

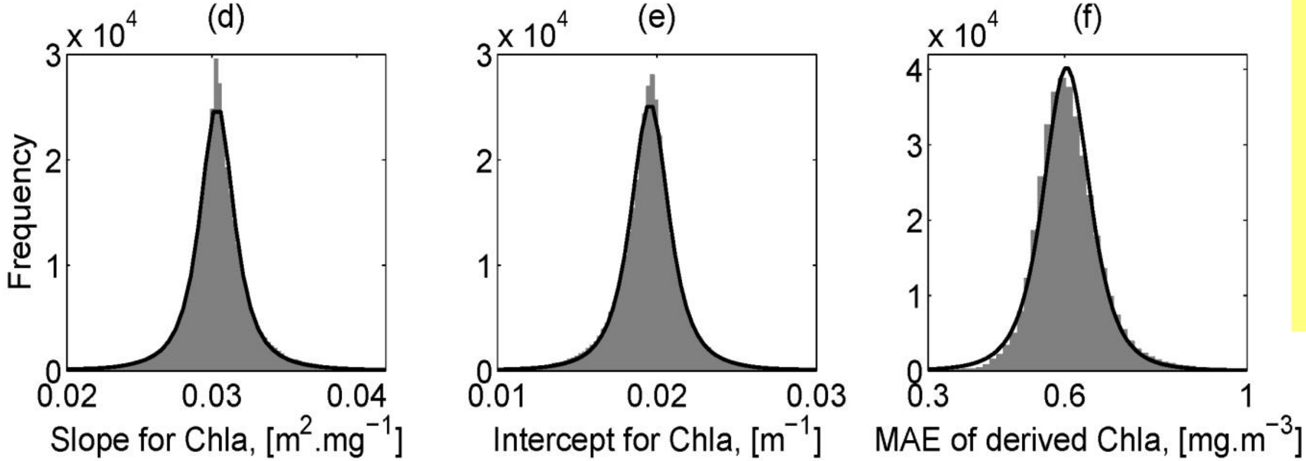
1- optimal subdivision of matchup data set into Cal and Val sets;

2- accuracy of calibration coefficients

3- probability distribution of the validation errors.



Determination coefficient, R^2, between measured and observed values of Chl*a* absorption coefficient from many Cal/Val setups. Light-grey coloured points represent the optimal Cal/Val pairs.



derived probability distributions (PDs) of calibration coefficients (d, e) and validation errors (f) for Chl*a* absorption per unit concentration

Salama et al., 2012, Biogeoscinces, 9, 2195–2201

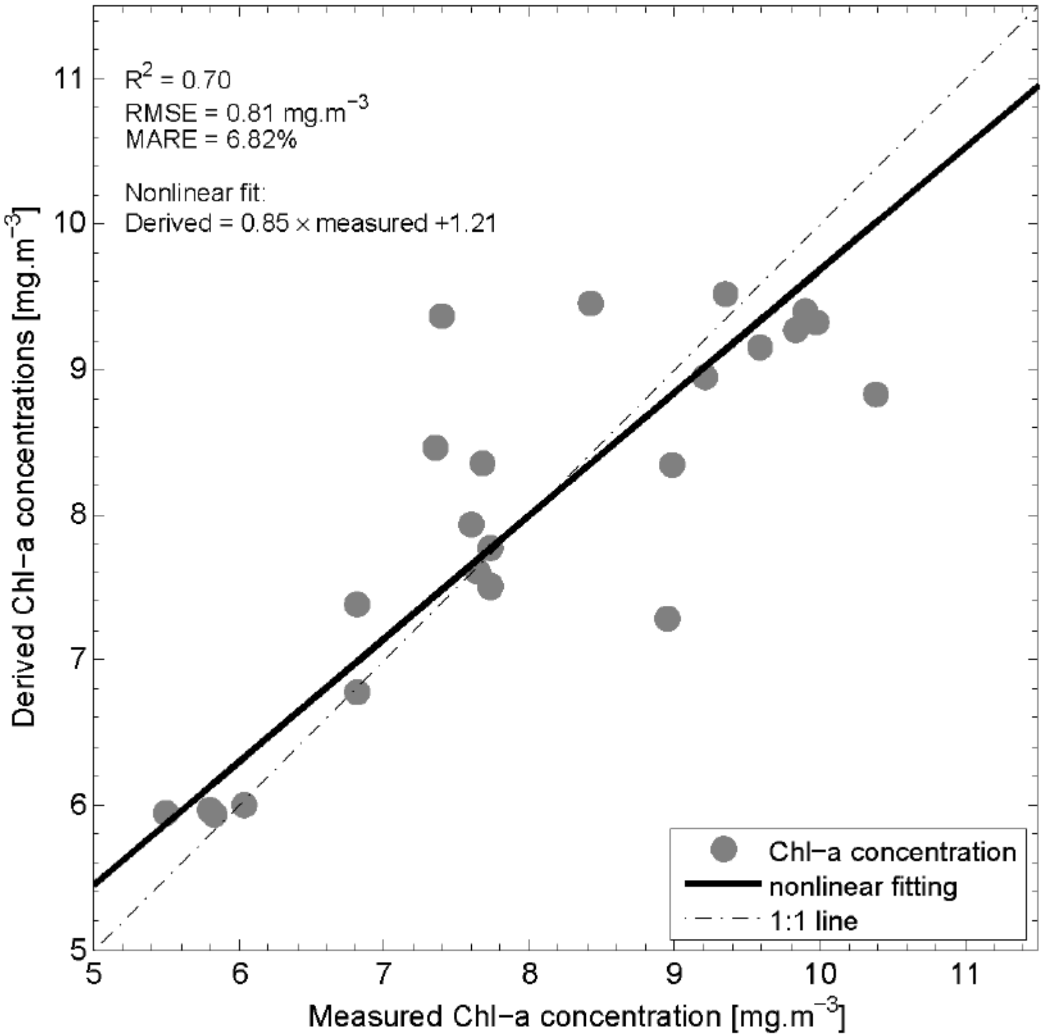
VERIFICATION: Chl-a

The validation was performed using in-situ radiometer and measure Chl-a values

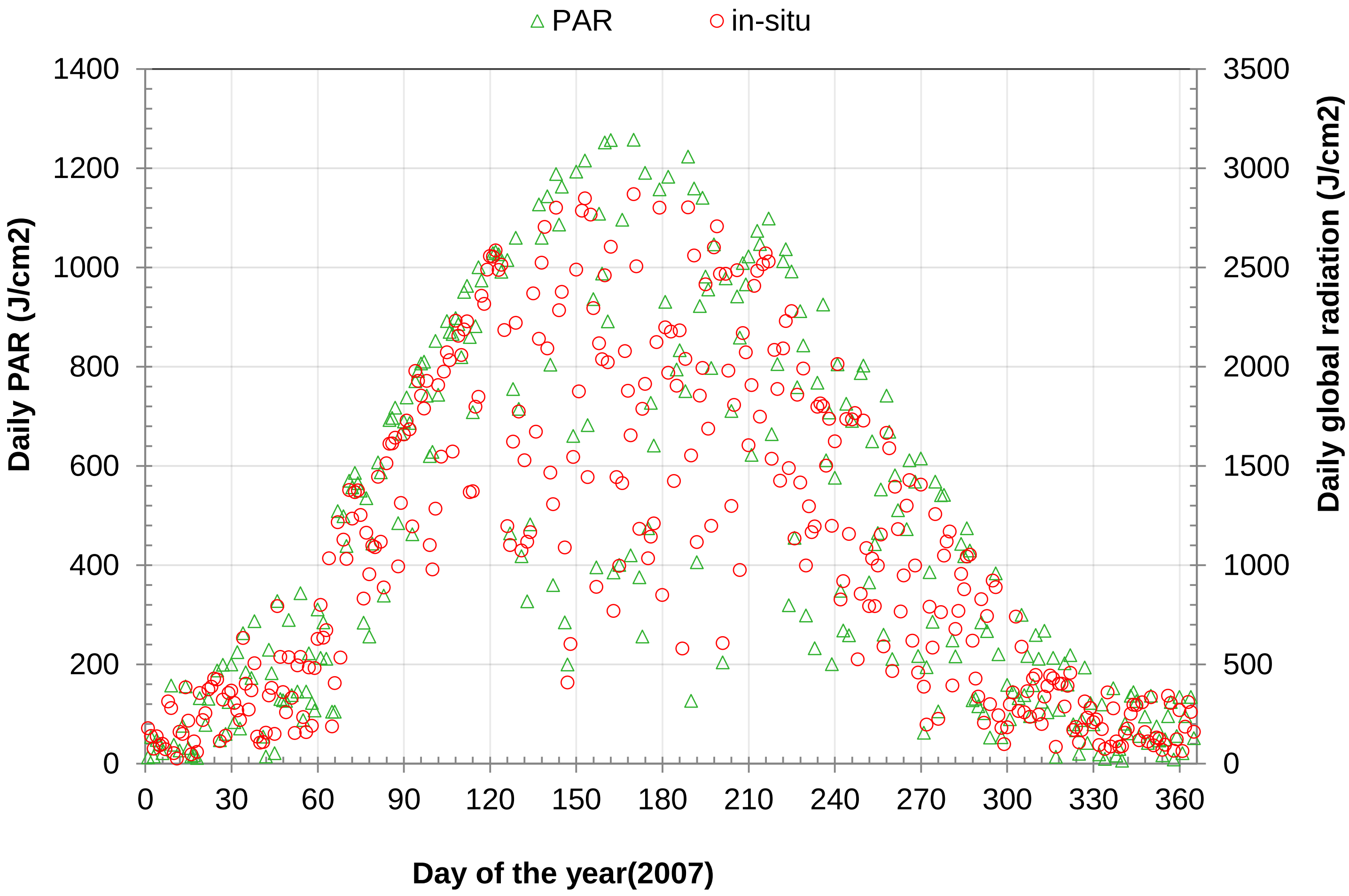
The radiometer measures the same quantity as EO sensors, MERIS: light!

We applied the MERIS retrieval model on field measured radiances to derive Chl-a concentration

These concentration are the compared to the measured values ate the same time

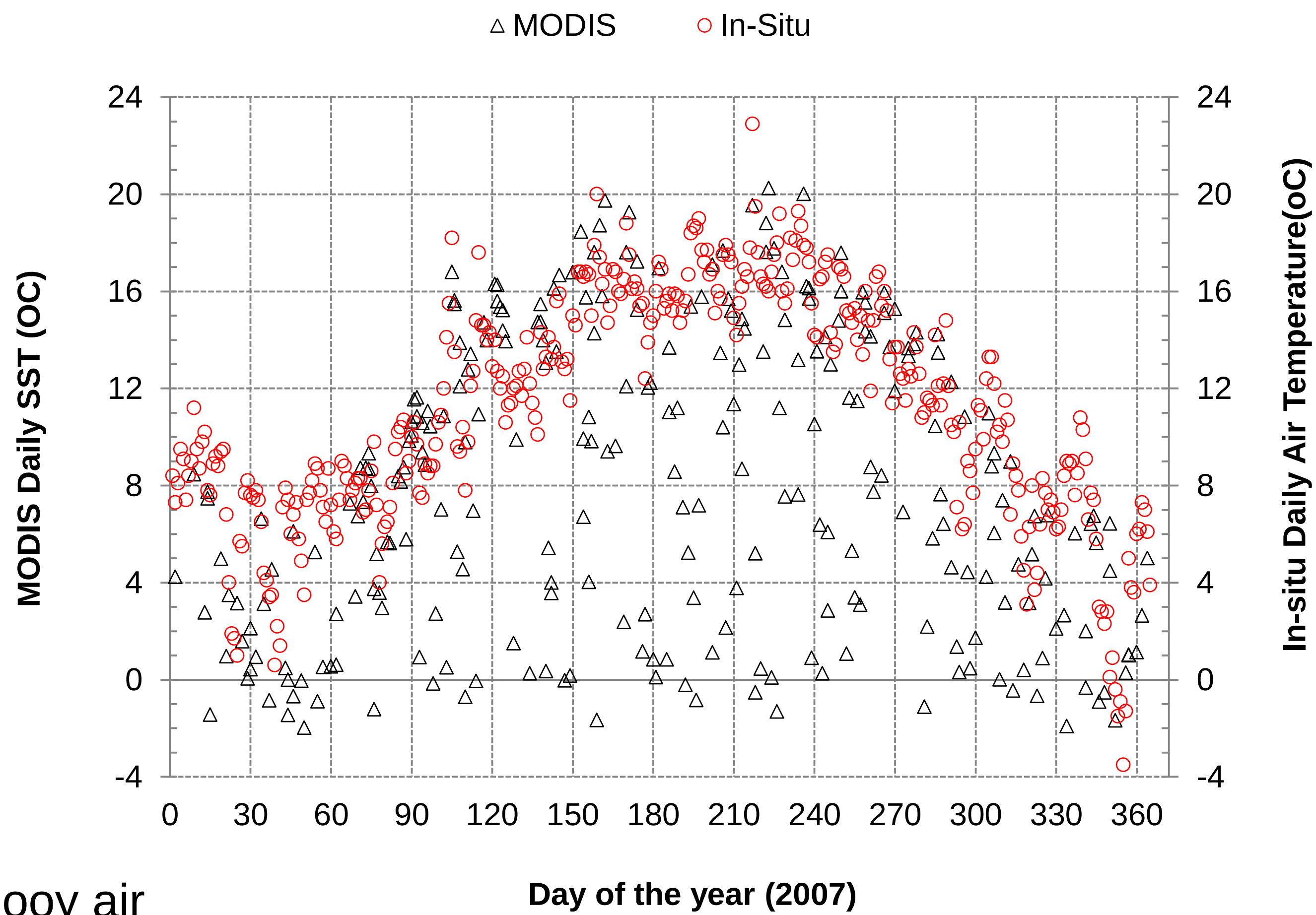


VERIFICATION: PAR



De Kooy global radiation KNMI

VERIFICATION: SST



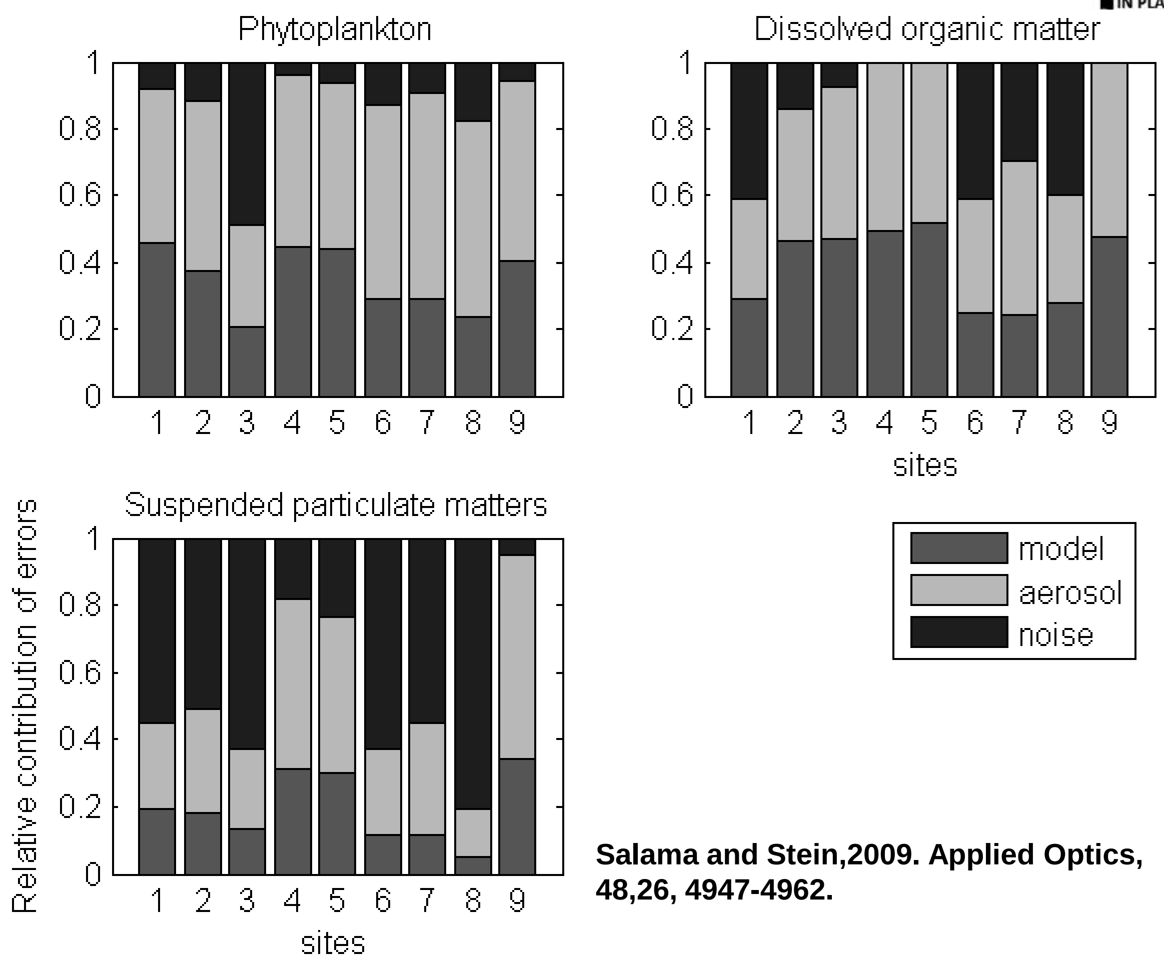
De Kooy air
tempreture
KNMI

HOW MUCH OF ALL THIS ADDS UP?

The total uncertainty in derived water quality indicators is the sum of three error component:

- atmosphere correction residuals
- sensor noise
- model inversion

$$\sigma_t^2 = \sigma_{atm}^2 + \sigma_{noise}^2 + \sigma_{inv}^2$$



Salama and Stein,2009. Applied Optics, 48,26, 4947-4962.

Error %	model	noise	atmosphere
Biomass	40	13	47
CDOM	41	13	46
SPM	45	5	50

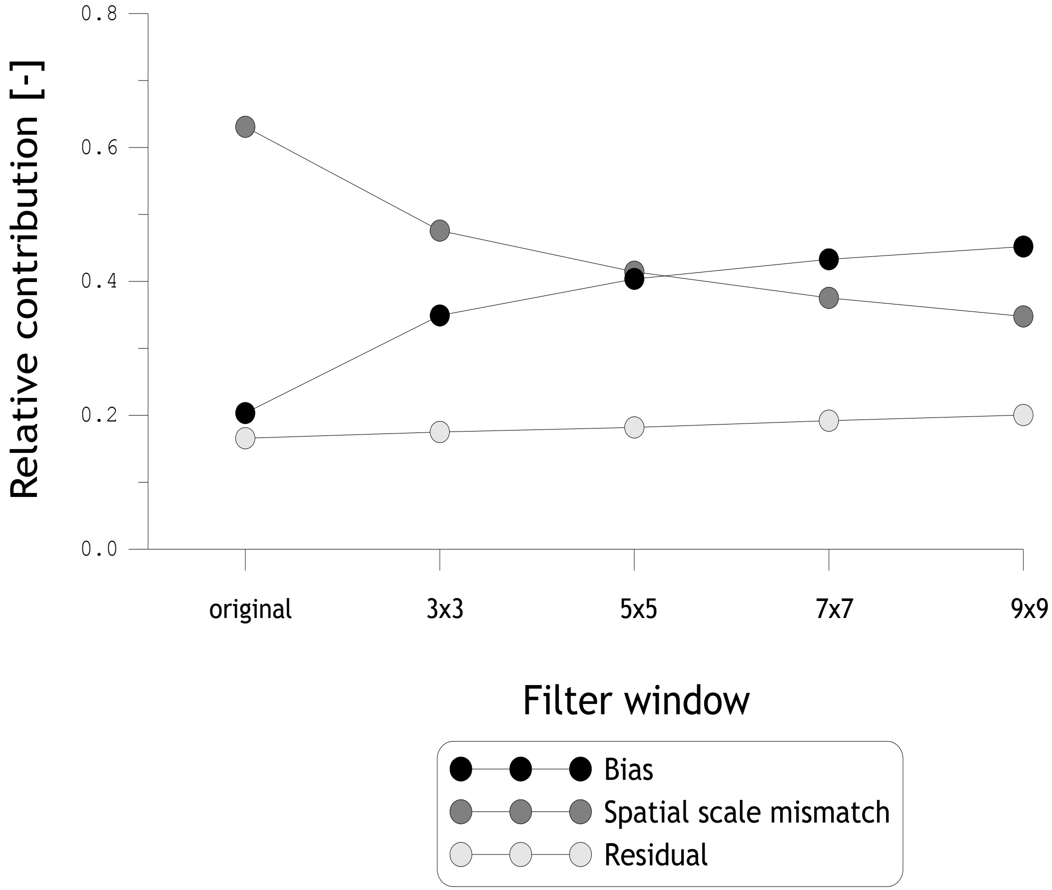
SPATIAL MISMATCH VERSUS ERROR?

- How much of this error component is actually due to the spatial mismatch between a point measurement (~2 m^2) and a pixel observation (~90,000 m^2)?

The relative contribution of three uncertainty sources averaged plotted against the kernel size of the median filter applied to the EO products:

Reduced resolution→ higher errors!!!

High resolution requires resolving the spatial mismatch!!!



Velde, Salama et al., 2012 Hydrometeorology, in press.

REMOTE SENSING OF NPP: WATER Chla based models

Vertically Generalized Primary Production Model (Behrenfeld, and Falkowski1997)

Remote sensing estimated

Chlorophyll-a concentration

Daily photoperiod

$$PP = 0.66125 \times P^B_{opt} \times \frac{PAR}{PAR + 4.1} \times Chl_a \times Z_{eu} \times D_{irr}$$

Primary Production

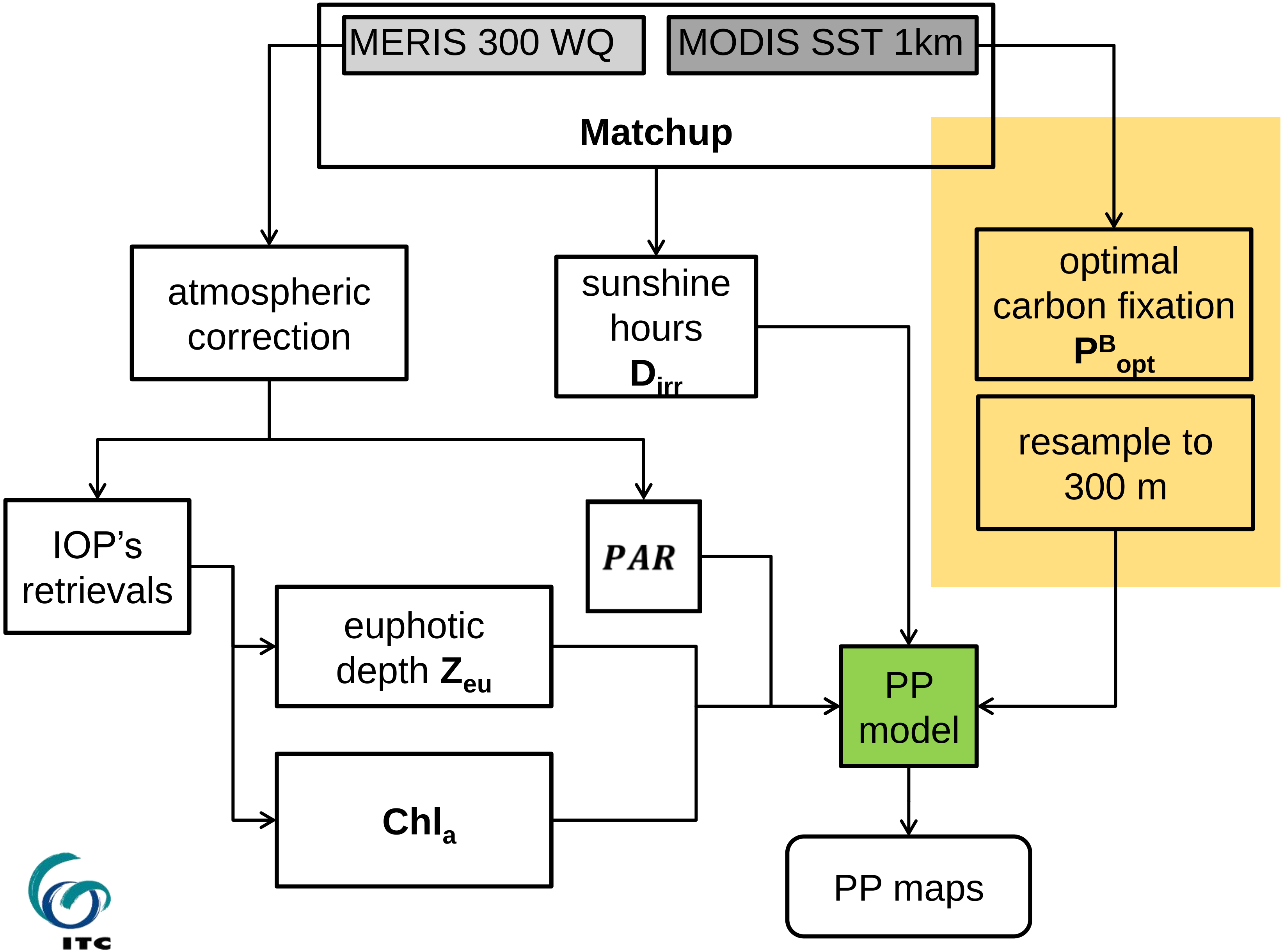
Photosynthetically Active Radiation

Euphotic depth → $Z_{eu} = 4.65/K_d$

Optimal daily carbon fixation rate →

$P^B_{opt} = f(SST) = 1.2956 + 2.749\times10^{-1}\,T + 6.17\times10^{-2}T^2 - 2.05\times10^{-2}T^3 + 2.462\times10^{-3}T^4 - 1.348\times10^{-4}T^5 + 3.4132\times10^{-6}T^6 - 3.27\times10^{-8}T^7$

PROCESSING CHAIN OF EO DATA



CARBON BASED MODEL

This model is based on the work of (Westberry et al. 2008)

The model is based on the ration Chl:C (chlorophyll-carbon ratio) and is estimated as

Chl:C=Chl: (bb_443-0.0003)*13000, [mgChl/mgC]

Chl and bb_443 are satellite derived Chl-a concentration and backscatering coefficient respectively.

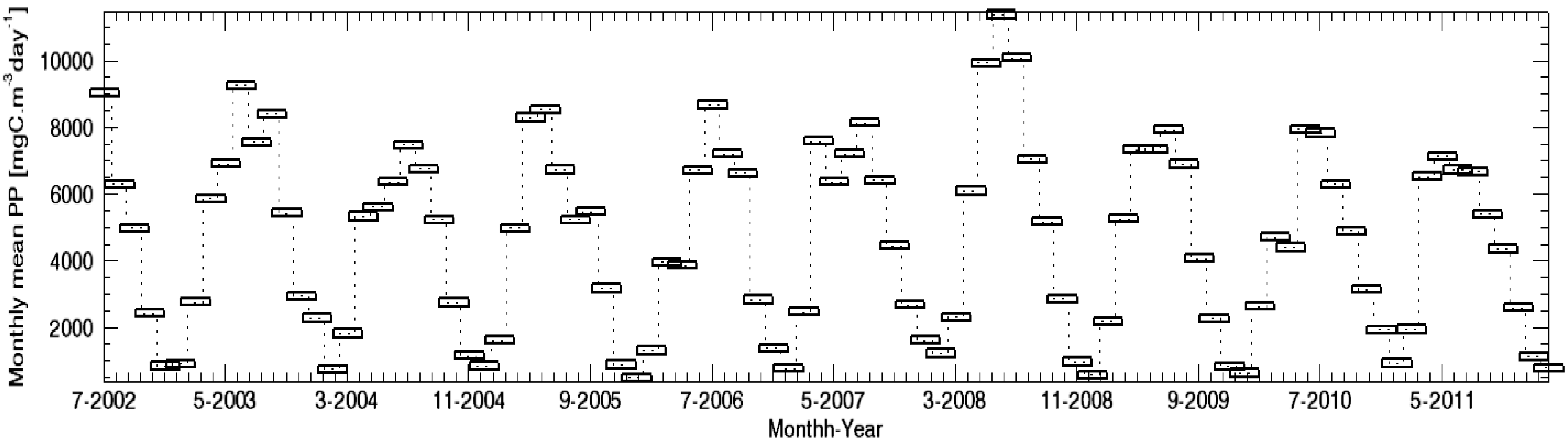
Chl:C_opt=0.022+(0.045-0.022)*exp(-3*PAR(z)); (Chl:C for optimal growth condition)

Mu=2*(Chl:C-0.0003)/(Chl:C_opt-0.0003) (growth rate per day d^{-1})

NPP=Mu*C [mg C m^{-2} d^{-1}]

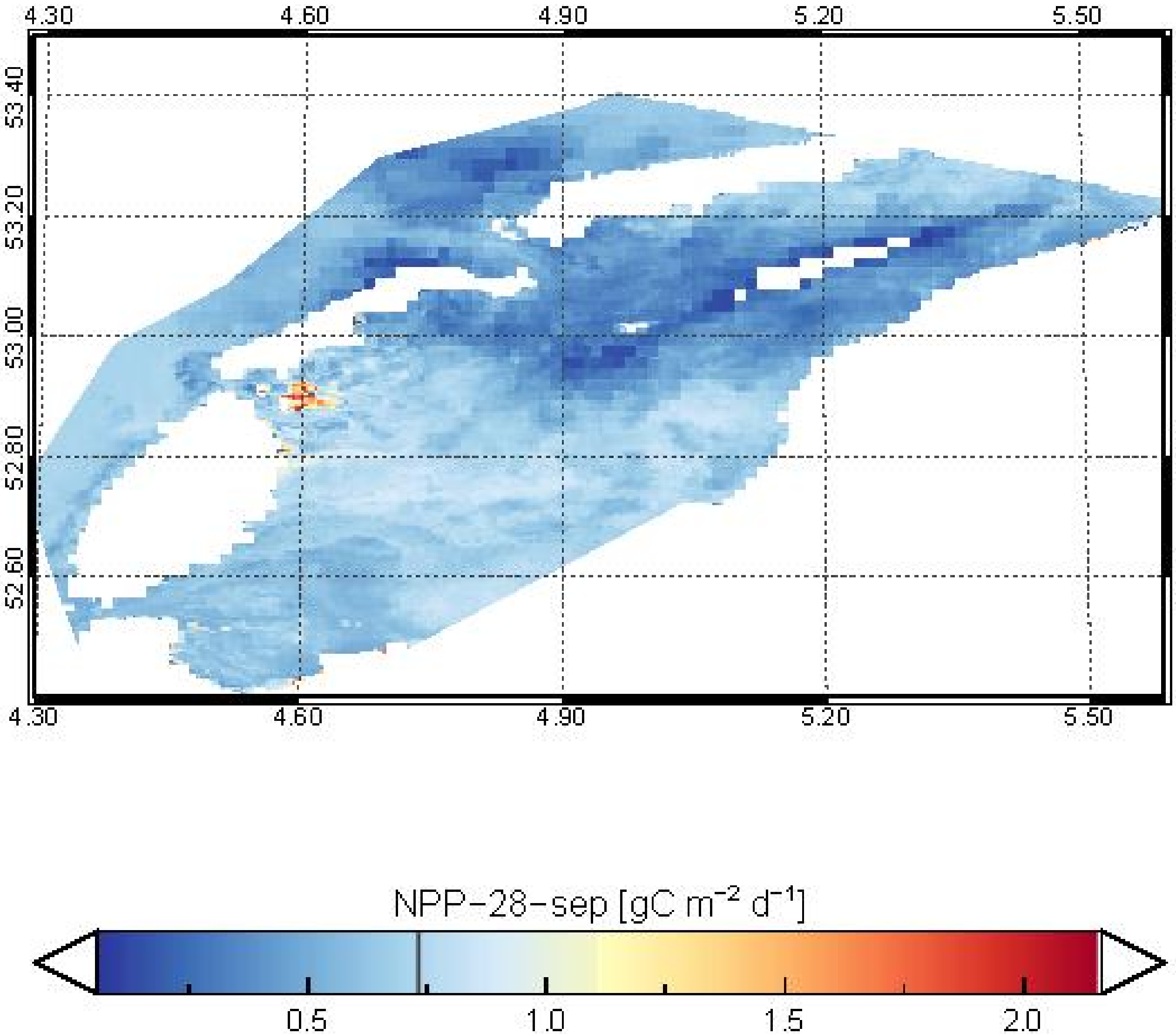
ADVANTAGES, OVER COARS RESOLUTION: SPATIAL

The monthly series of primary production in the Dutch Wadden Sea 1.5 pixel in MODIS global products



ADVANTAGES, OVER COARS RESOLUTION: SPATIAL

Spatial variation of PP in the Wadden Sea as resolved by MERIS

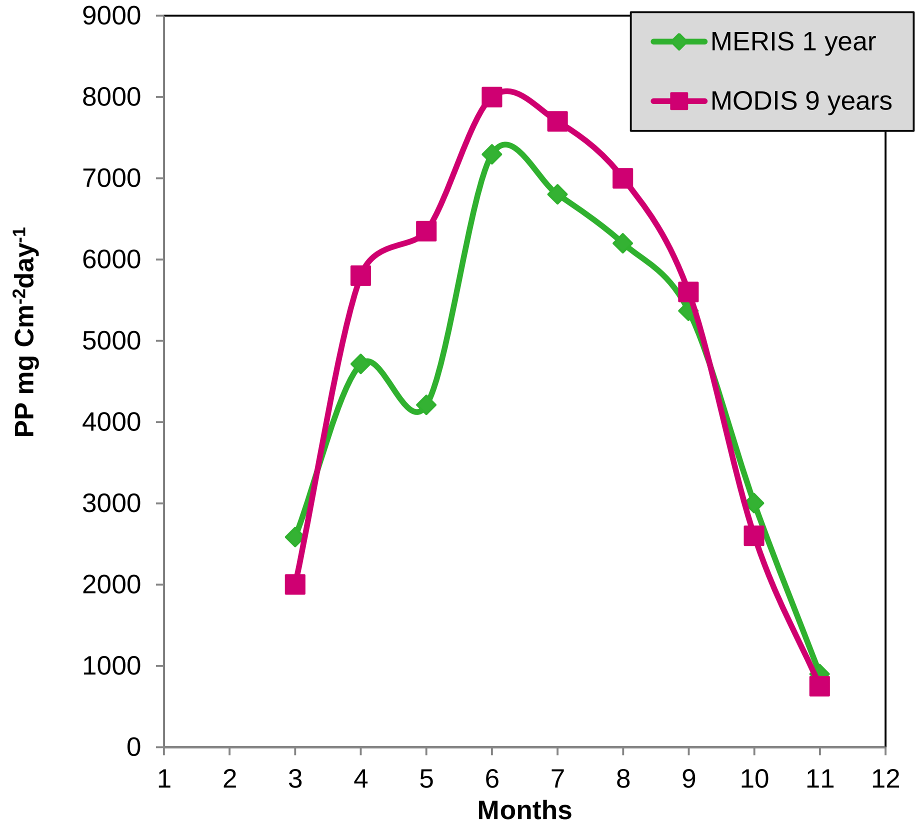


ADVANTAGES, OVER COARS RESOLUTION: TEMPORAL

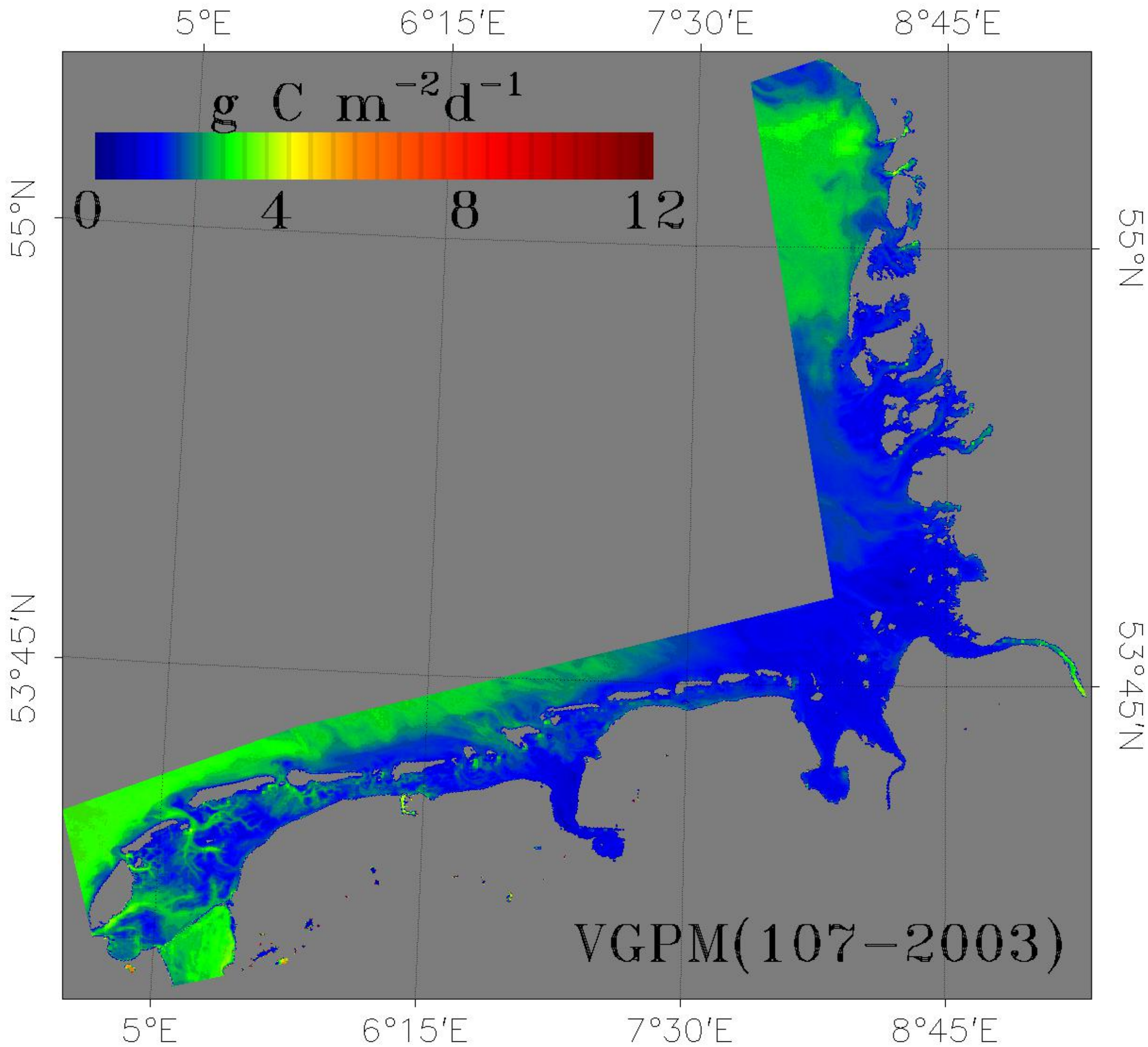
The climatology is computed for MODIS by averaging the same month over a 10-year period.

MERIS monthly mean for one year….

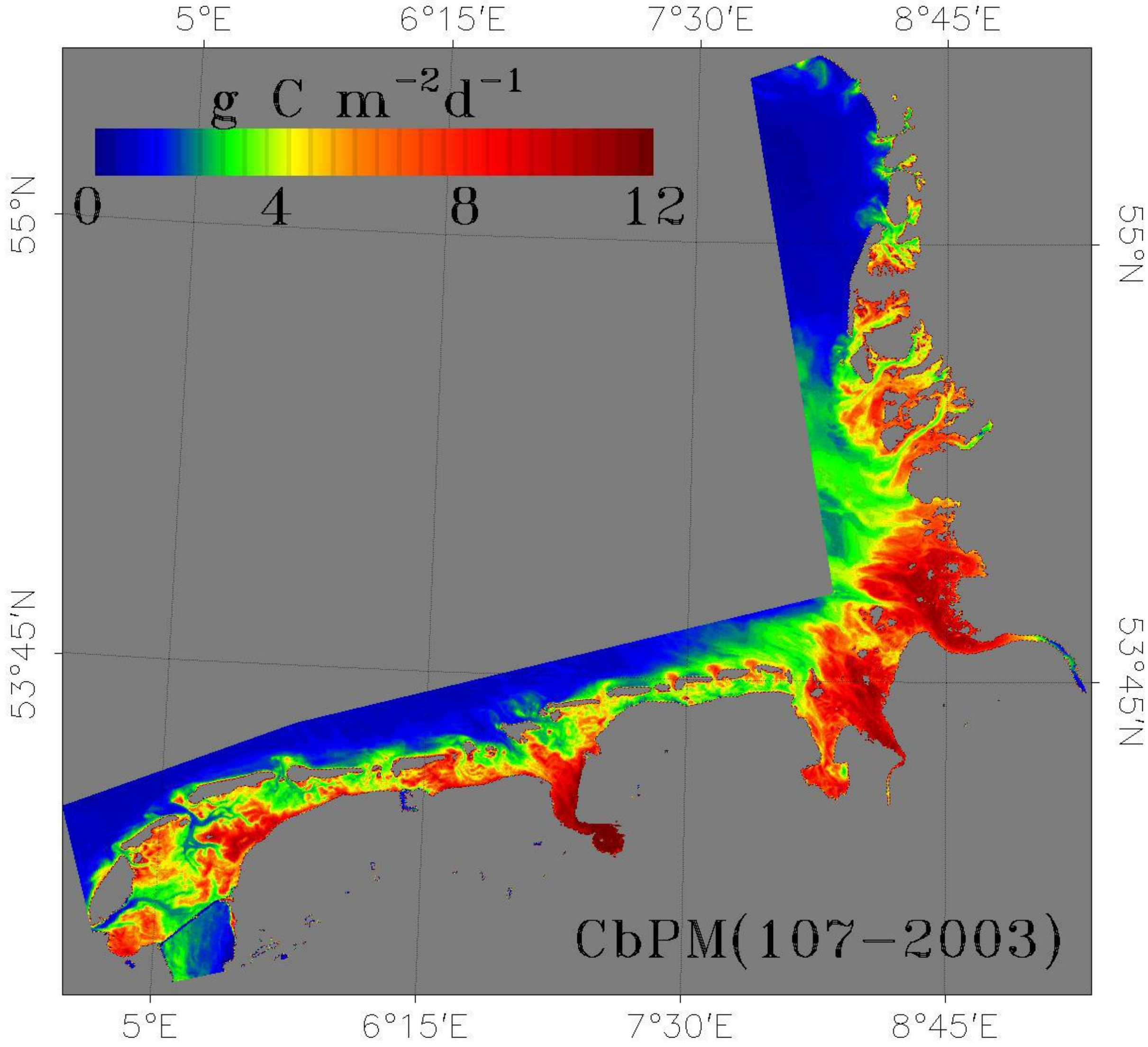
In average the fit is okey but the timely averaged MODIS fails to distinguish the spring bloom…..



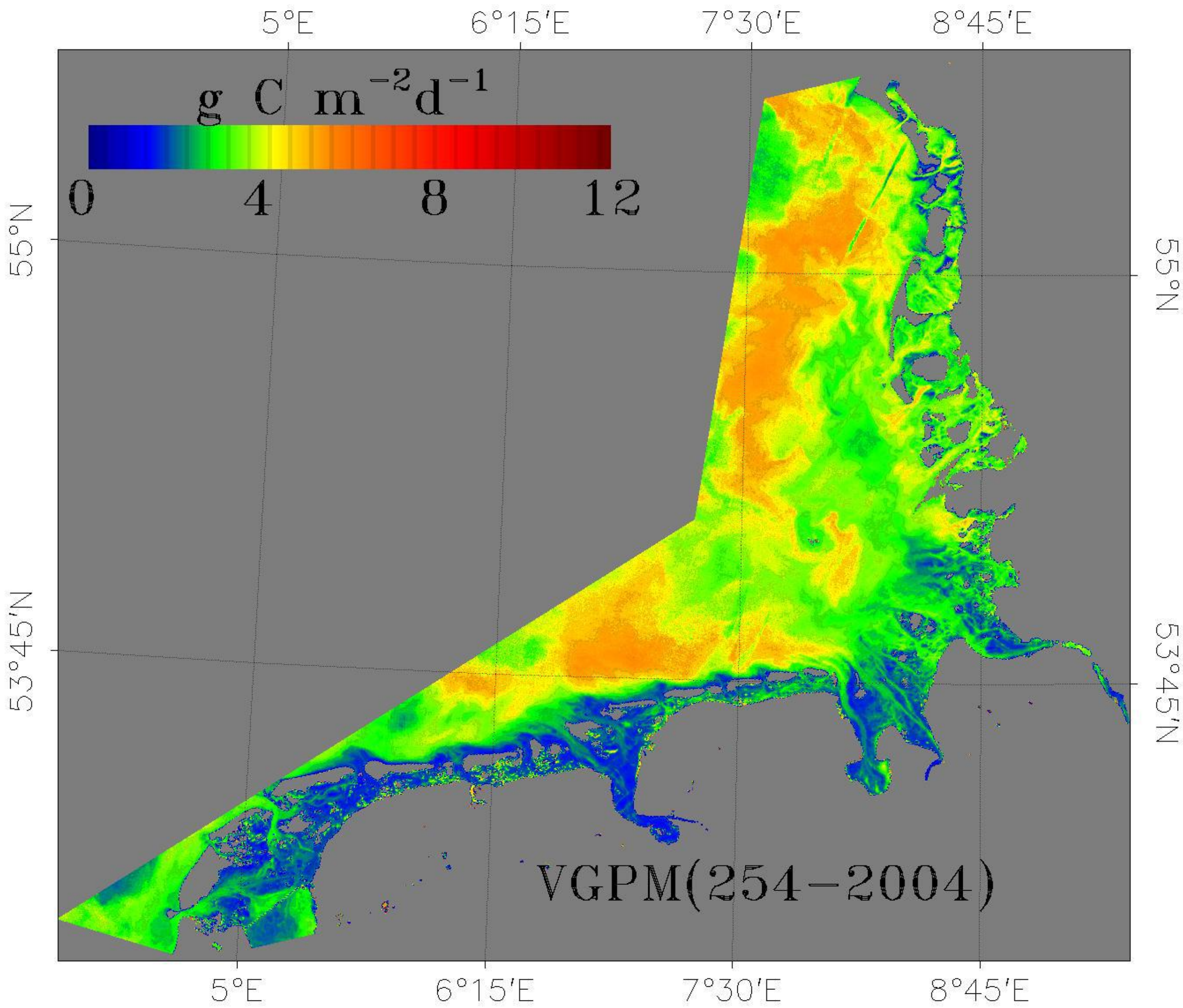
Which one? Welcome MERIS



Which one? Welcome MERIS

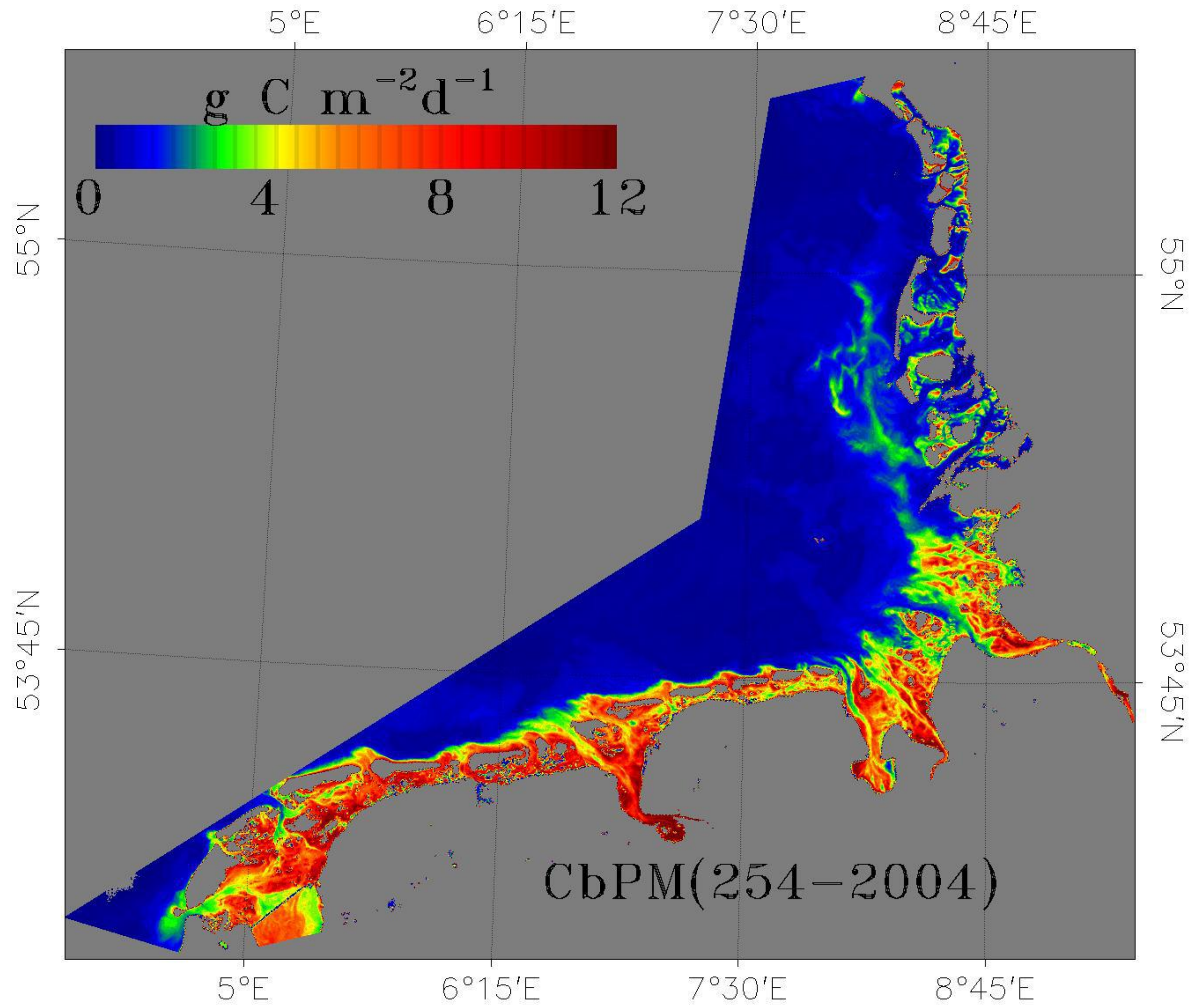


Which one?

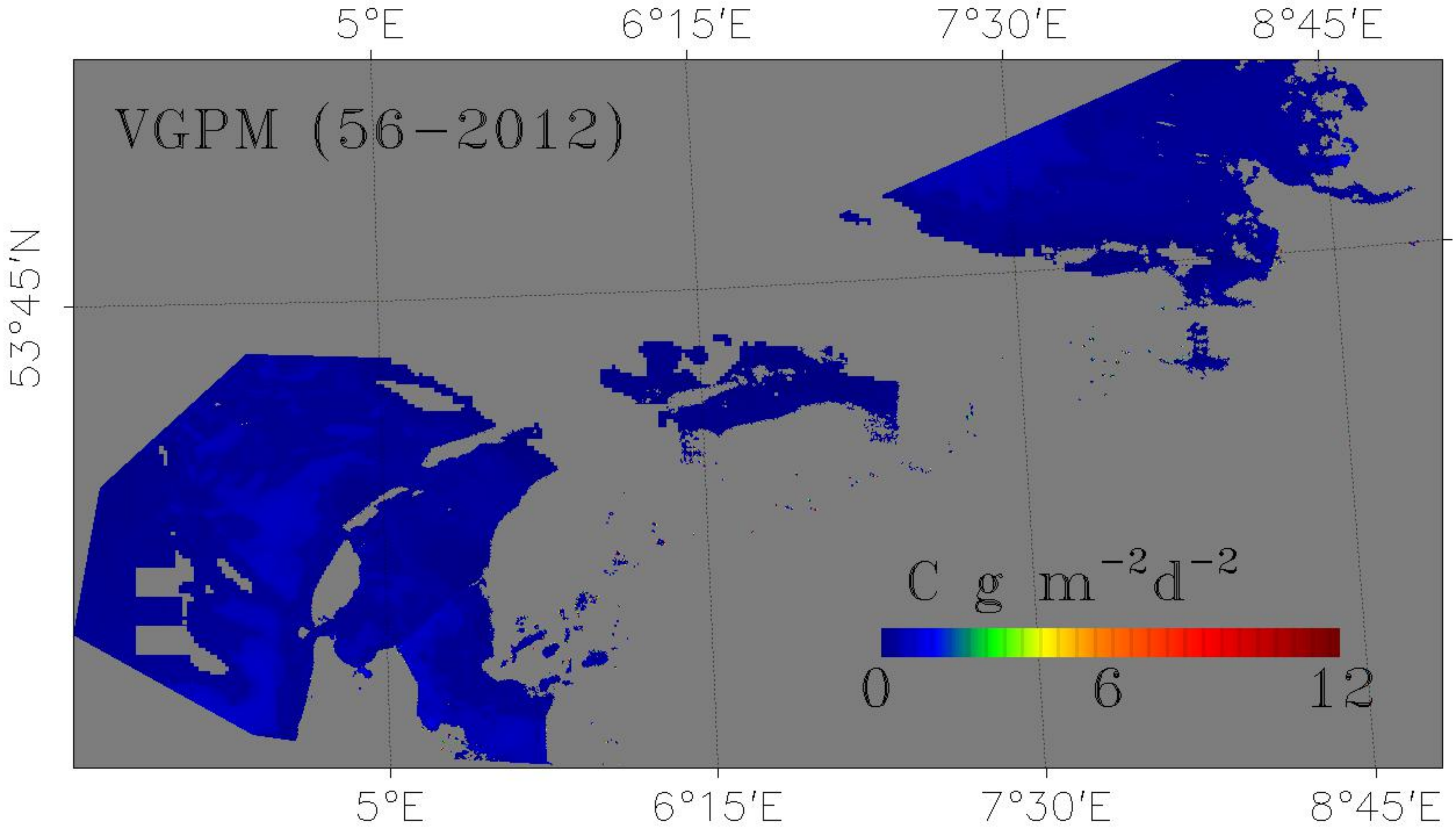


5°E
6°15′E
7°30′E
8°45′E
g C m^{-2}d^{-1}
0
4
8
12
55°N
53°45′N
55°N
53°45′N
VGPM(254−2004)
5°E
6°15′E
7°30′E
8°45′E

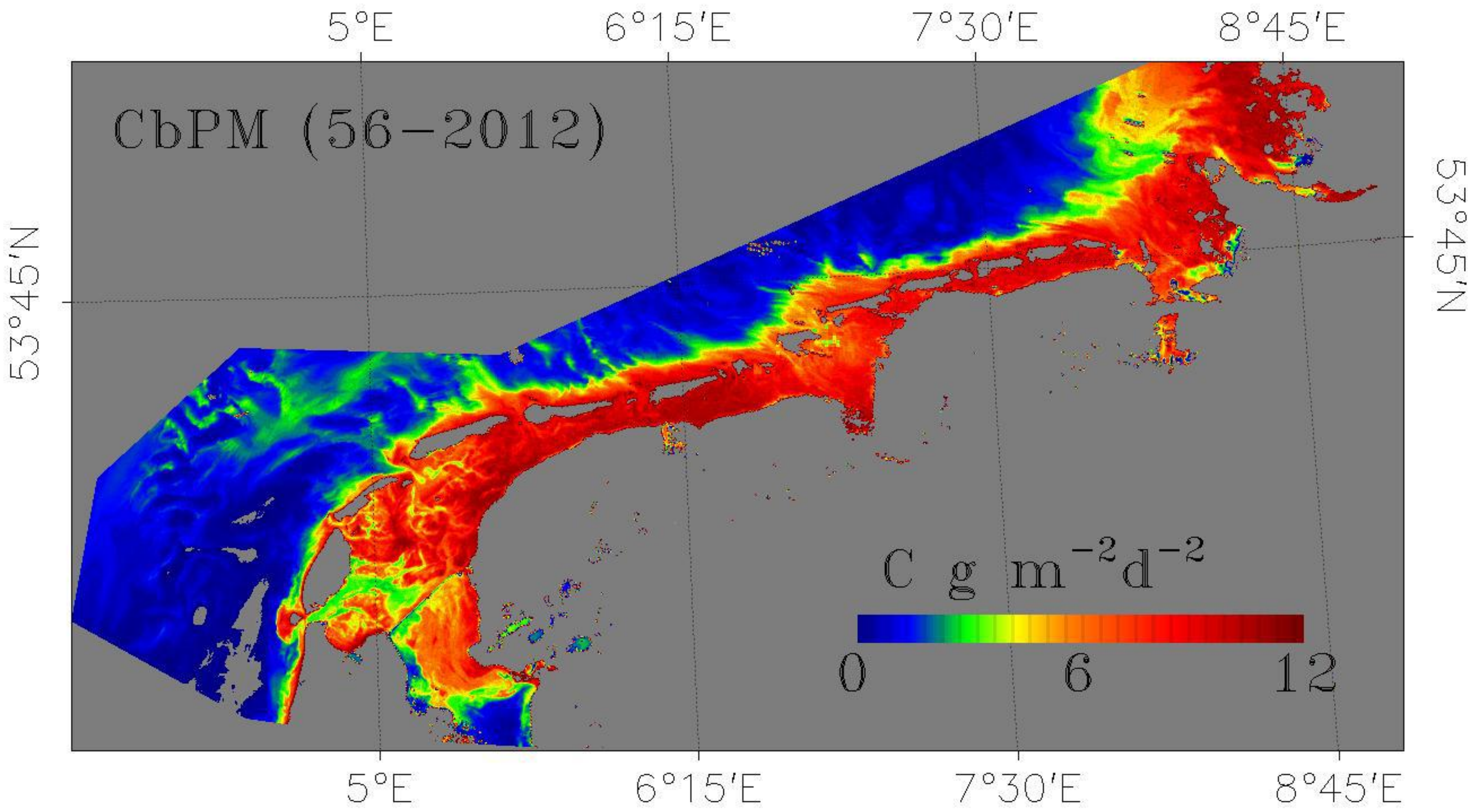
Which one?



Which one? Goodbye MERIS



Which one? Goodbye MERIS



PRIMARY PRODUCTION OF MUDFLATS

- Primary production of mudflat follows, the same procedure :
- Model of Platt et al., 1976

EO estimated

$$PP_{mud} = \boxed{Chl_a} \cdot \boxed{P^B_{opt}} \left(1 - e^{(\alpha^B \cdot \boxed{E_z} / P^B_{max})}\right)$$

P^B_{opt} optimal daily carbon fixation rate, estimated from Mud Surface Temperature;

α^B the photosynthetic efficiency is set to 0.0264 (mgC mgChl$_a^{-1}$ hr^{-1} (umol m^{-2}s^{-1}) $^{-1}$);

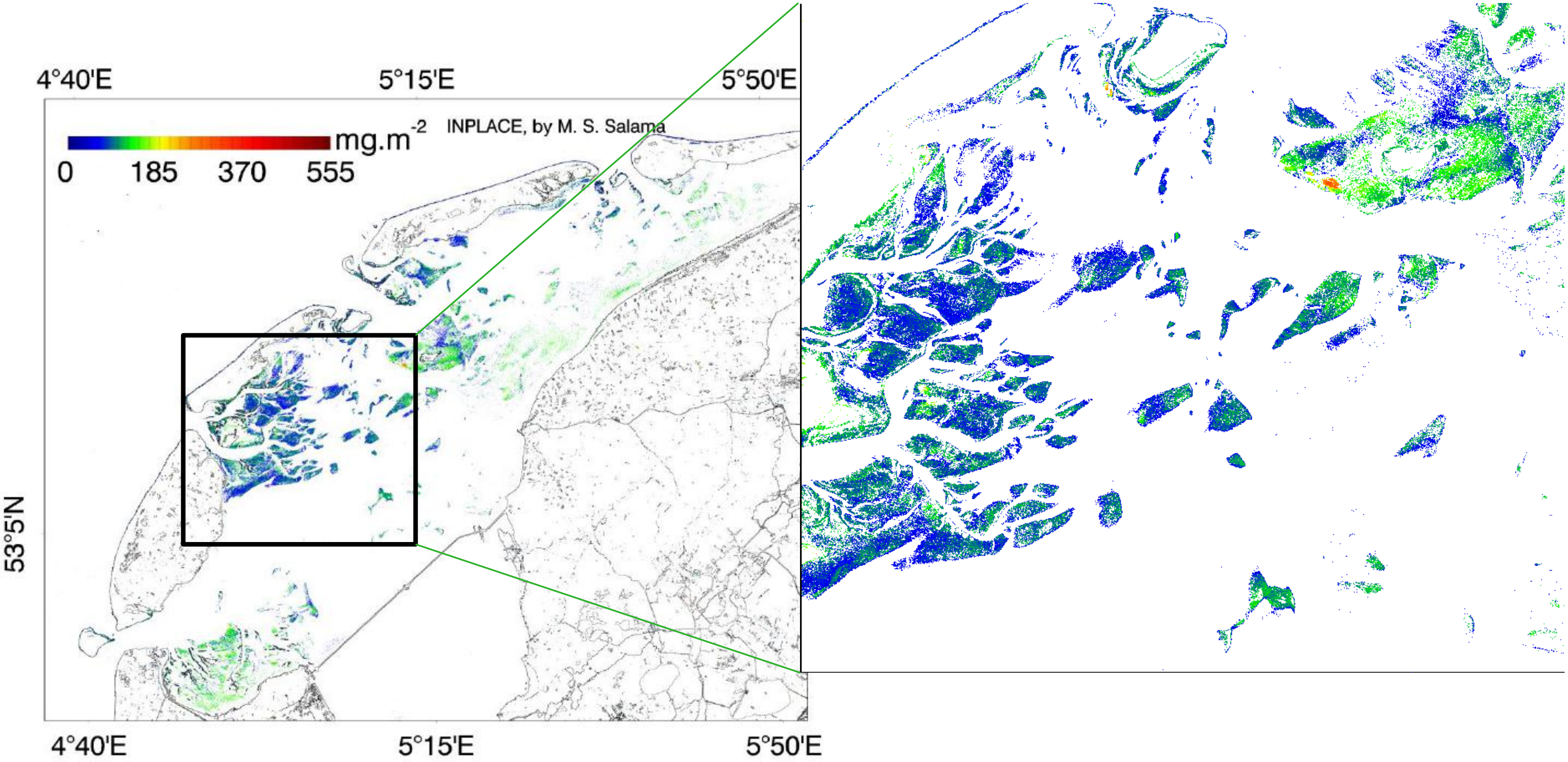
Chl_a is estimated from NDVI (Kromkamp et al,2006);

E_z amount of light at depth Z (usually used 2 mm) is approximated from Chl$_a$

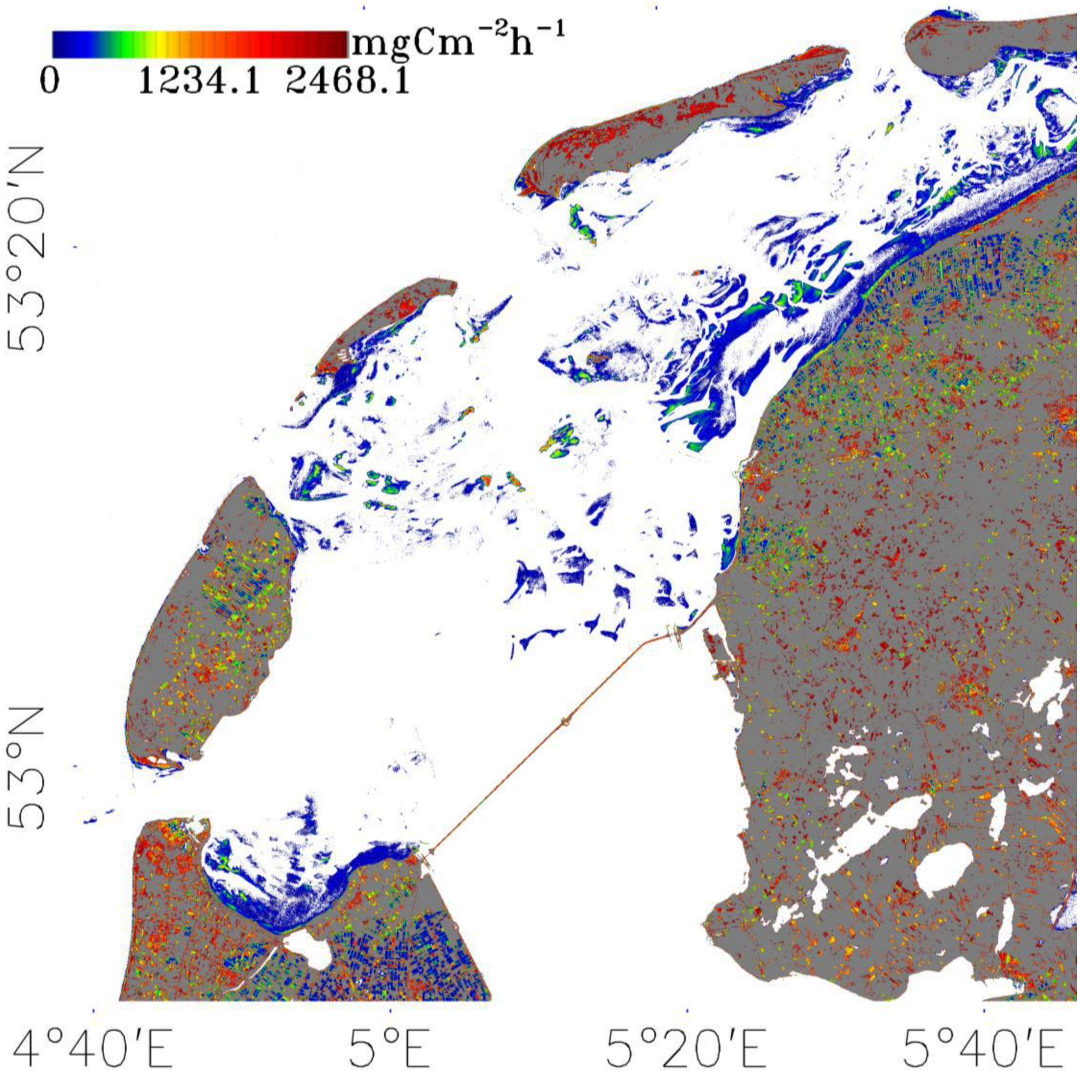
ESTIMATING CHL-A

Estimate Chl-a from the Normalized difference vegetation index (NDVI)= (Red-Green)/(Red+Green) (Kromkamp et al., 2006).

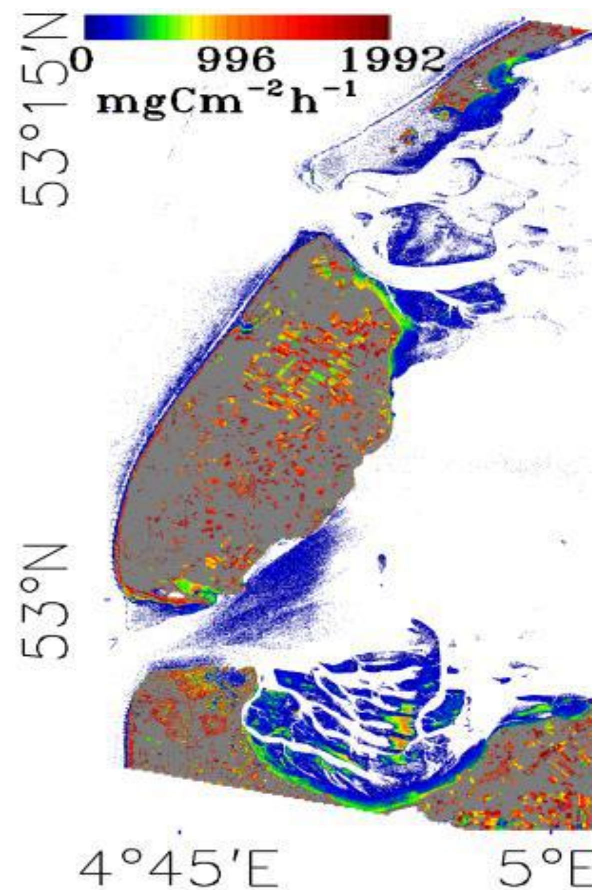
Sensor :LANDSAT ETM, 30 m resolution!



PP of MUDFLATS



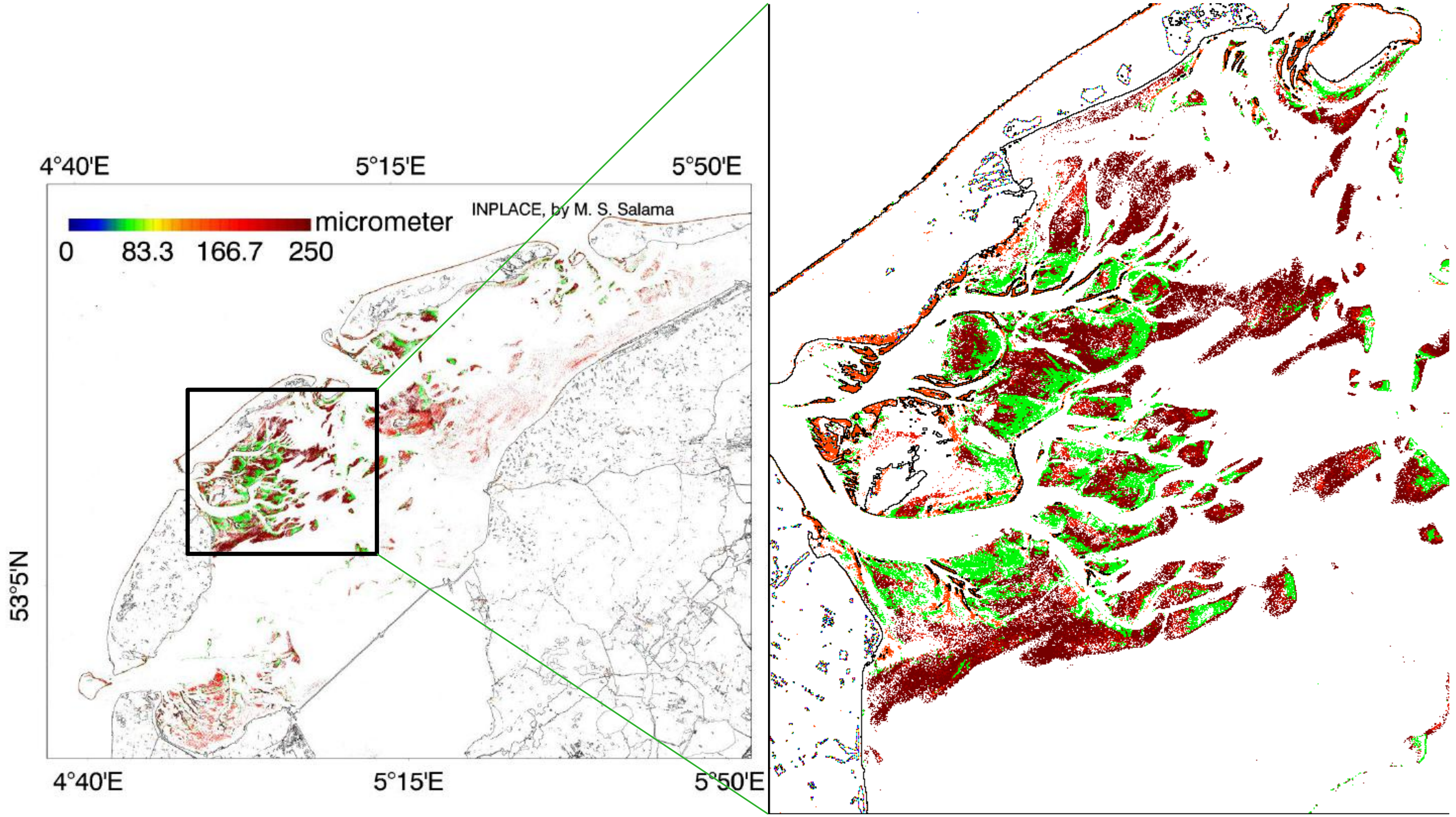
LANDSAT



ASTER

MUD FLATS: BY PRODUCTS

Based on the supervised classification we can estimate the particle size distribution (PSD) of the surface layer of mudflats.



PRELIMINARY CONCLUSIONS

Errors due to correction are the major source of uncertainty in the derived Chla and PP maps.

NPP verification is a challenge in coastal water.

Although the seasonal variation of NPP is well understood and driven by temporal changes in light, temperature and nutrient availability, the reason for the interannual variability in primary production is often unclear, and quantitative measures of this cycle in time and space might help resolve the reasons behind the interannual variability in productivity.

Which is better chl*a* or carbon based models? Although point validation is possible (as argued by the authors of these models), verifying the correctness of the spatial distribution is the challenge.

ACKNOWLEDGMENT

- NWO : National Program Sea and Coast Research (ZKO);
- IN PLACE project (Integrated Network for Production and Loss Assessment in the Coastal Environment), involved team and the crew of the NAVICULA and the STERN at NIOZ;
- PROTOOL project (Automated Tools to Measure Primary Productivity in European Seas) and involved team;
- KNMI - Koninklijk Nederlands Meteorologisch Instituut;
- European Space Agency (ESA);
- National Aeronautics and Space Administration (NASA) USA;
- Flemish Institute for Technical Research (VITO)

Questions?

IN PLACE

Primary Production Project

NWO - ZKO "Carrying Capacity" Program