Website

Toolbox

Climate from Space

Open Data Portal

Knowledge Exchange Climate Change Initiative

Machine learning in (and beyond) the ESA Climate Change Initiative

Carsten Brockmann[1], CCI Knowledge Exchange Coordinator

With contributions from S. Mecklenburg[2], Ed Pechorro[2], P. Kershaw[3], R. Doerffer[1,4], D. Müller[1], R. Quast[1], J. Wevers[1], L. Bock[5]

[1]Brockmann Consult GmbH, [2]ESA, [3]UKRI-STFC CEDA, [4]HEREON, [5]DLR

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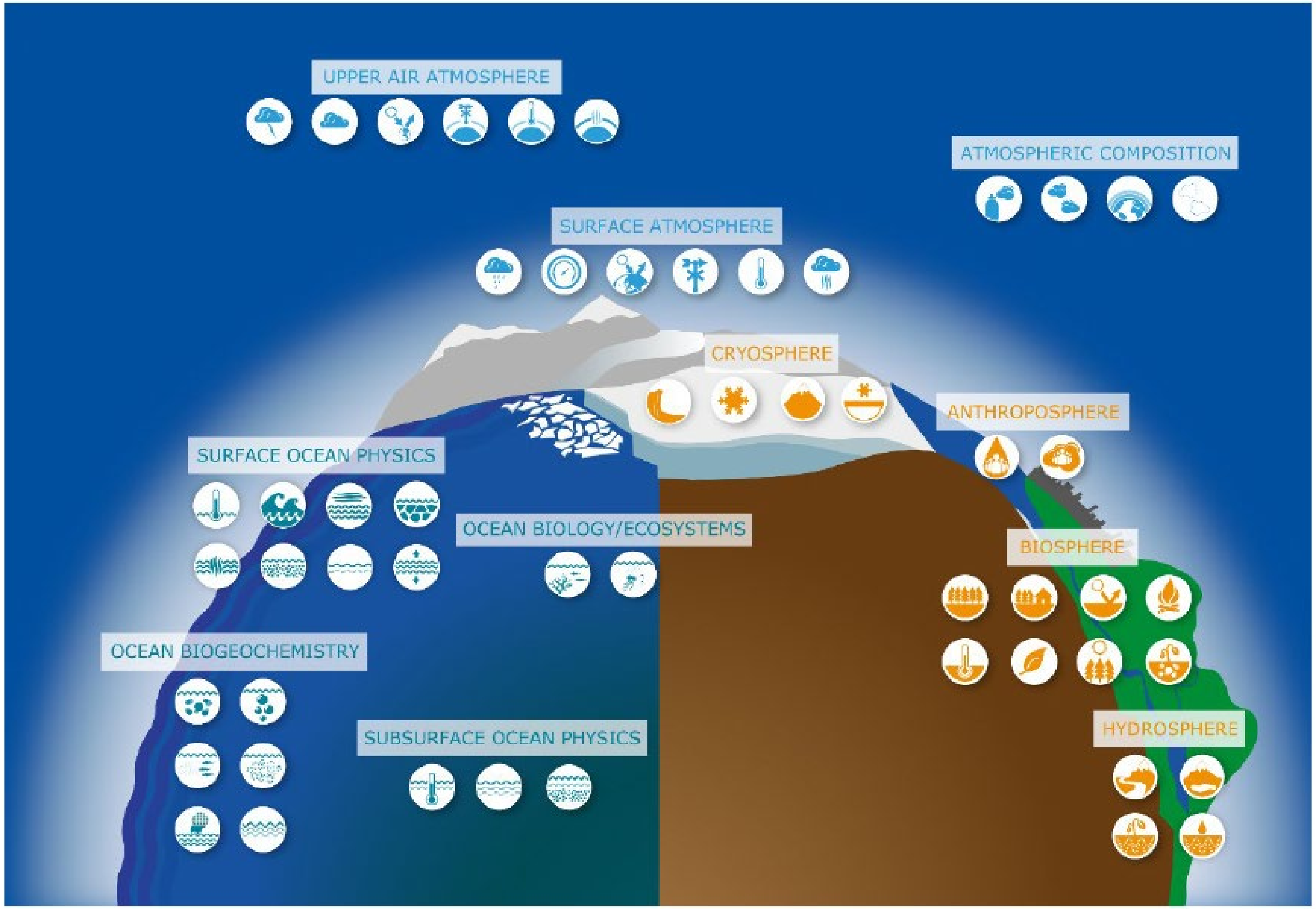
Knowledge
Exchange
Climate
Change
Initiative

Essential Climate Variables (ECV)

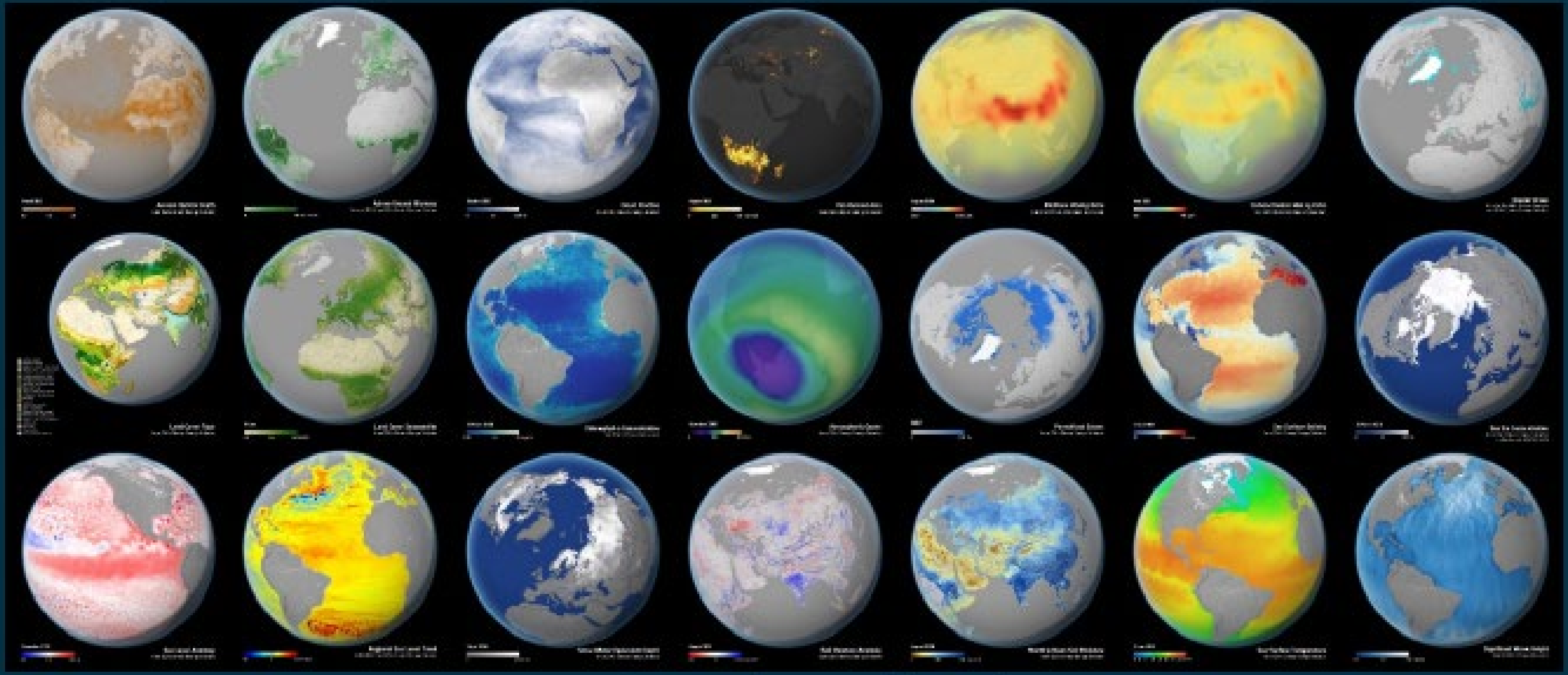


- An **ECV** is a physical, chemical or biological variable or a group of linked variables that critically contribute to the the characterisation of the Earth‘s climate
- ECV datasets provide the **empirical evidence** needed to understand and predict the **evolution of climate**, to guide **mitigation** and **adaptation** measures, to assess risks and enable attribuion of climate events to underlying causes, and to underpin climate services. They are required to **support the work of the UNFCCC and the IPCC**
- ECVs need to be
  - **Relevant**
  - **Feasible**
  - **Cost effective**

From S. Mecklenburg (ESA Climate Office)

ESA Climate Change Initiative (CCI)

WMO defined **54** Essential Climate Variables
36 benefit from space observations
21 generated by ESA Climate Change Initiative



climate modelling user group cci

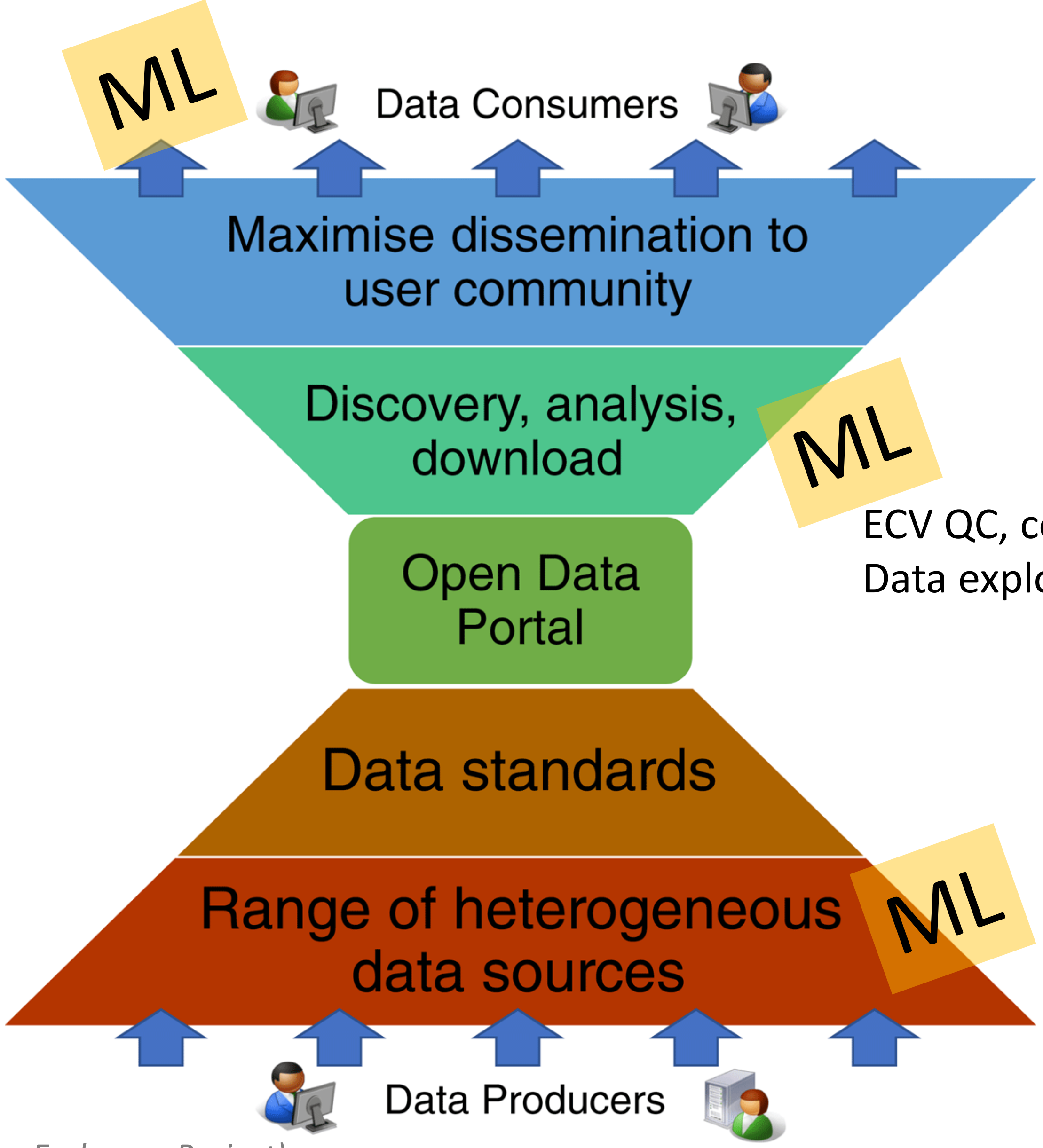
sea level budget closure cci

reccap-2 cci

From S. Mecklenburg (ESA Climate Office)

CCI Open Data Portal and Opportunities for ML

Combination with non ESA data, Climate analysis, forecasting and scenarios



ECV QC, consistency
Data exploration, single and cross-ECV analyis

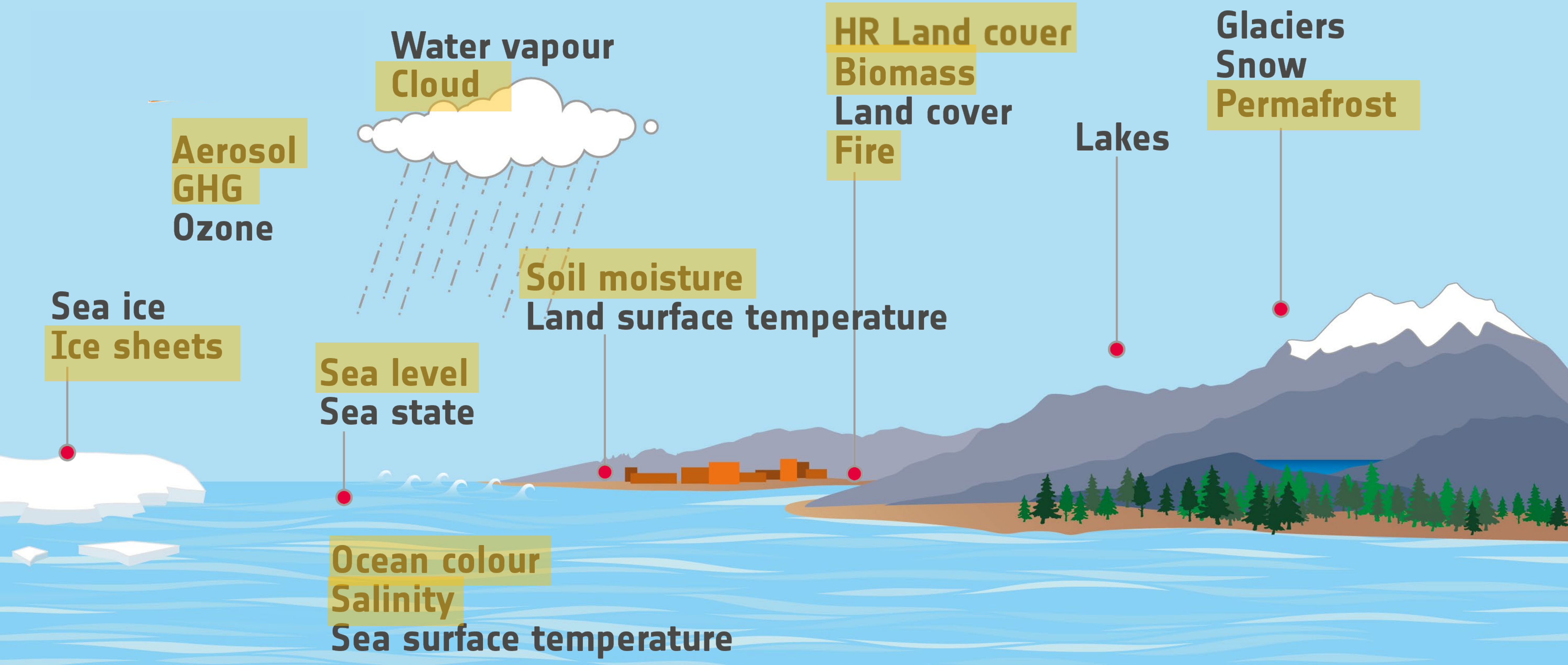
ECV production
(L1 -> L2 -> L3 processing)

Adapted from P. Kershaw (CEDA, CCI Knowledge Exchange Project)

CCI ECV Projects

ML

From ESA Climate Office *Note on CCI & AI* 2019 Q4 (v0.23) & 2021 Q4 (v1.0)
- Includes - Current use ; Planned use ; Resource gaps for AI ; Future Concepts



From E. Pechorro (ESA Climate Office)

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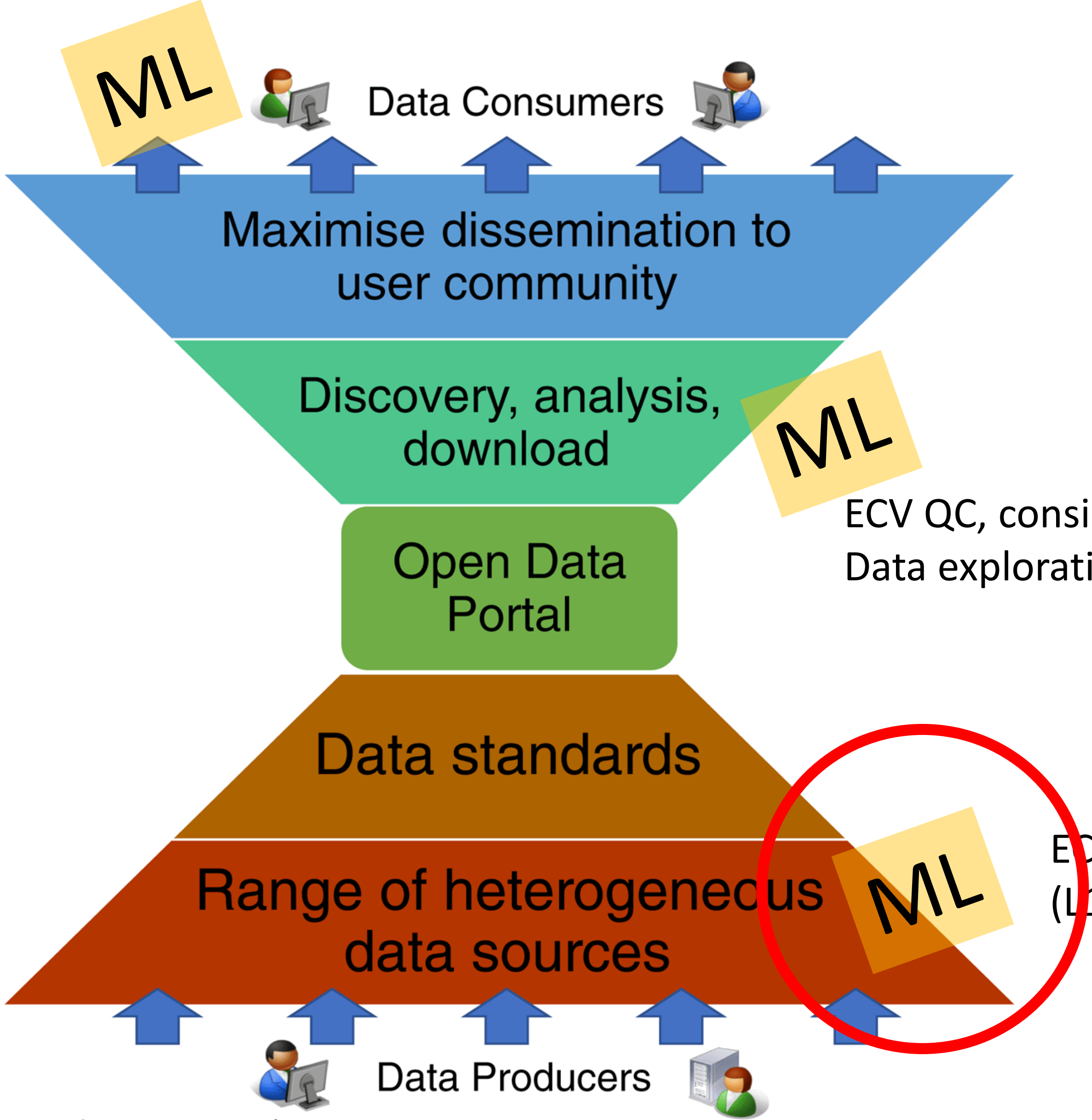

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ECV production
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Adapted from P. Kershaw (CEDA, CCI Knowledge Exchange Project)

ML in ECV Production Algorithms – Cloud Masking

- More than Cloud Masking – Pixel Identification as first step in a processing chain
  - cloud, snow, land, water, …
  - critical cases: semi-transparent clouds, fractional snow cover, mangroves, muddy water, …
  - relevant for basically all ECVs using optical EO data: ECVs: Clouds, Aerosols, LandCover, Fire, Snow, Ocean Colour,

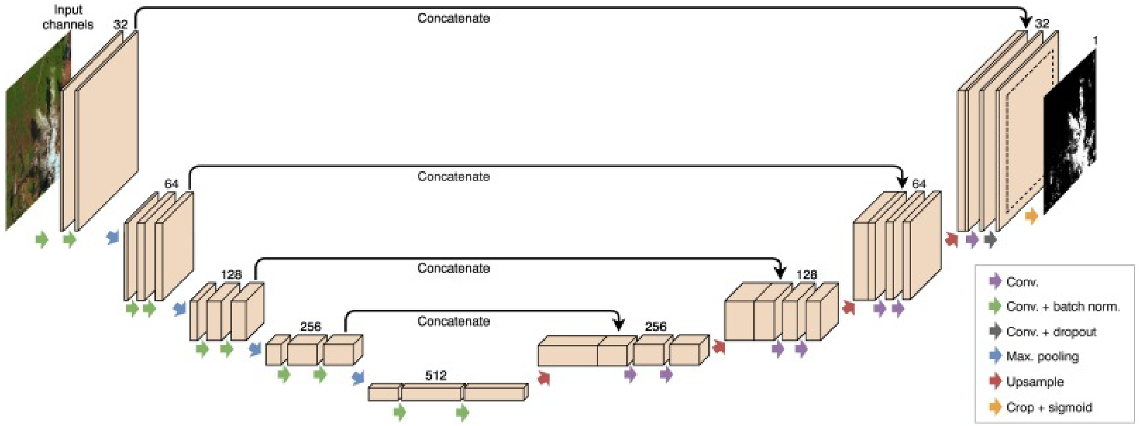
Axel Rohkohl, fotocommunity

www.beyondarctic.com

© pixabay.com | Ravini

- Classical ML task:
  - Traning data set with labelled pixels
  - Various methods applied: DL, NNs, RF, SVM, …

- Most important: training dataset



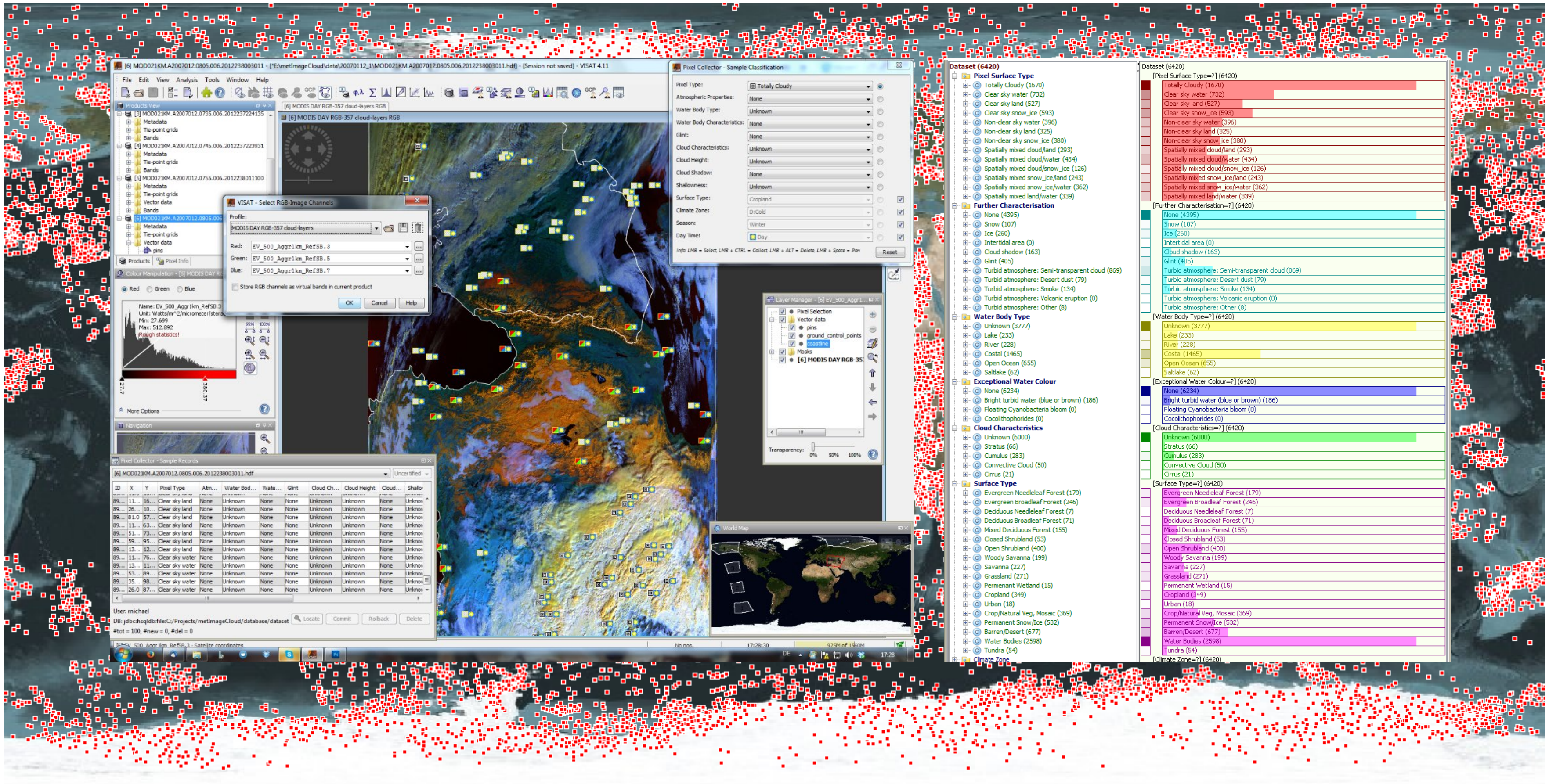
Jepsen et al, 2019

PixBox – Manually Selected Pixel Collection

SLSTR night time collection

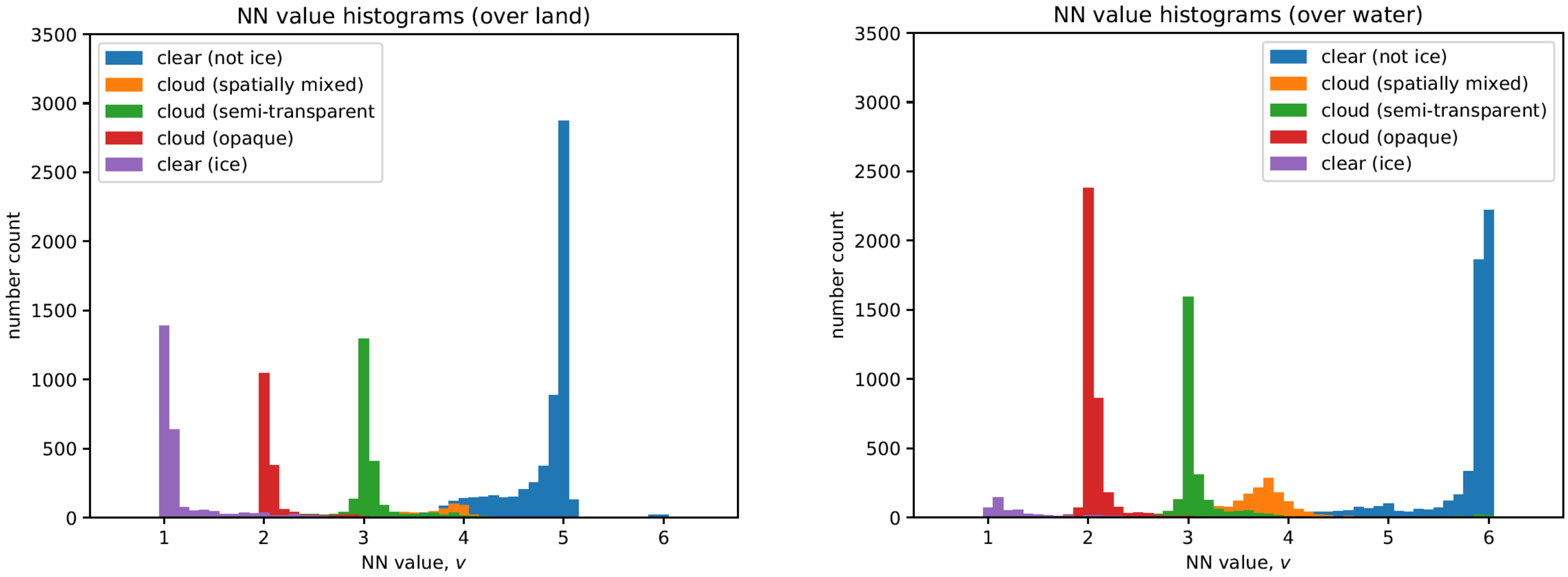
44.500 night time pixels collected

194 products from 44 different orbits from 3 different day (15.12.2016, 15.03.2017, 15.06.2017)



NN Training - Separability

Sentinel-3 OLCI



From R. Quast(Brockmann Consult)

Validation

PixBox (validation sample)

EO

Class	Clear all Land	Clear Mountain	Clear Urban	Clear Desert	Clear Salt-Lake	Clear Other Land	Cloud	Sum
CLEAR	2841	160	116	450	8	2107	267	5949
CLOUD	717	289	65	60	29	274	4282	5716
Sum	3558	449	181	510	37	2381	4549	11665

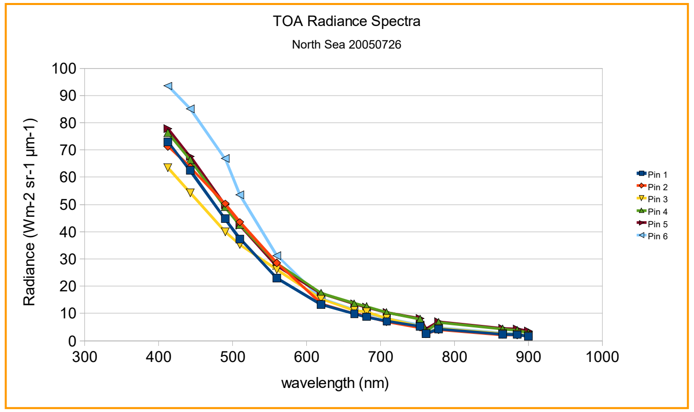
EO

Class	Clear	Opaque	Thick	Med	Thin	Sum
CLEAR	3688	1277	74	1010	746	6795
CLOUD	306	3912	394	1499	268	6379
Sum	3994	5189	468	2509	1014	13174

From J. Wevers (Brockmann Consult)

Ocean Colour - Physically based ML

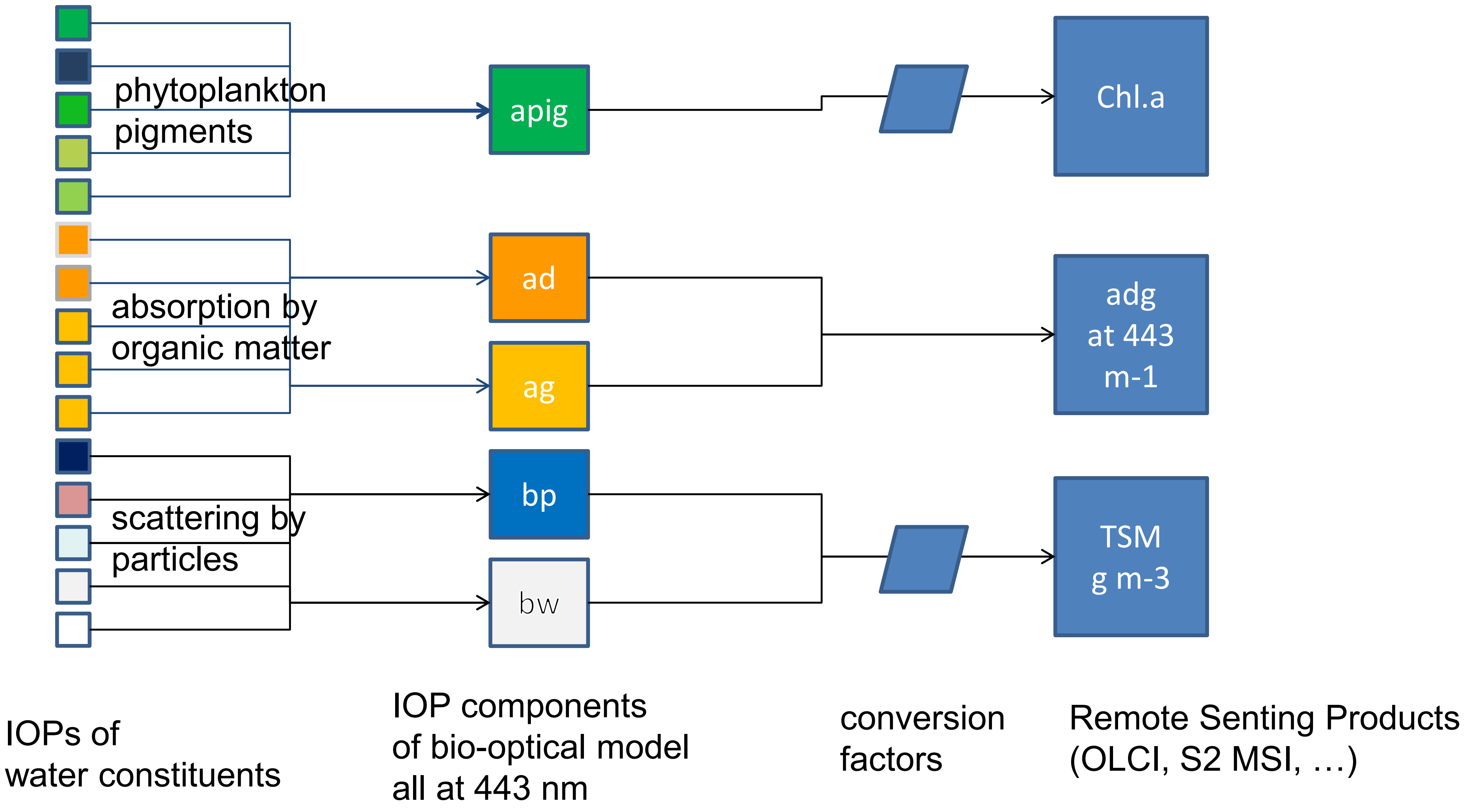
The problem:
Inversion of underdetermined highly non-linear radiative transfer equation



air molecules
different aerosols
thin clouds
contrails
Sky reflectance
Sun glint
foam
floating material
Suspended particles
dissolved organic matter
Vertical distribution
chlorophyll
Bottom reflection
different phytoplankton species

From R. Doerffer (Brockmann Consult & HZG Research Centre)

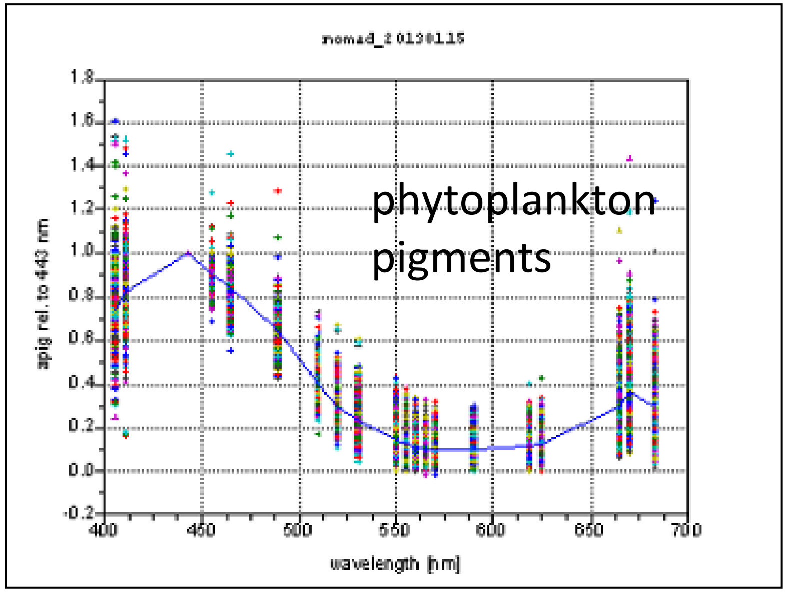
Bio-Optical Model

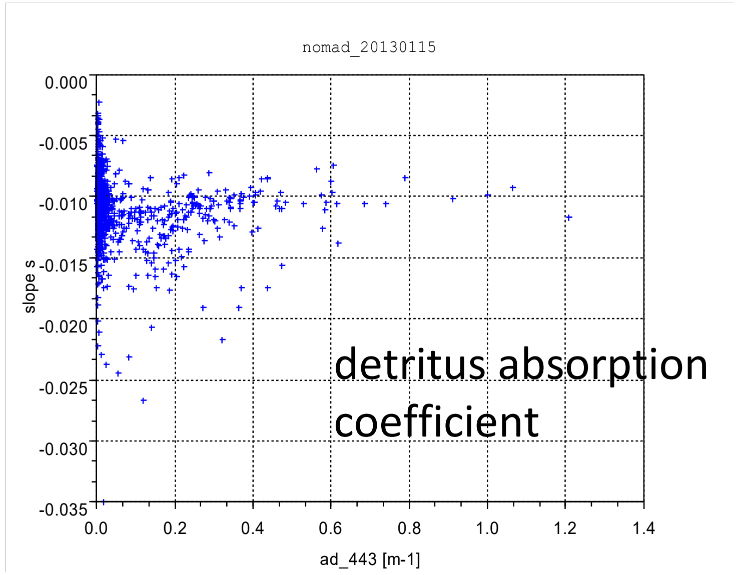


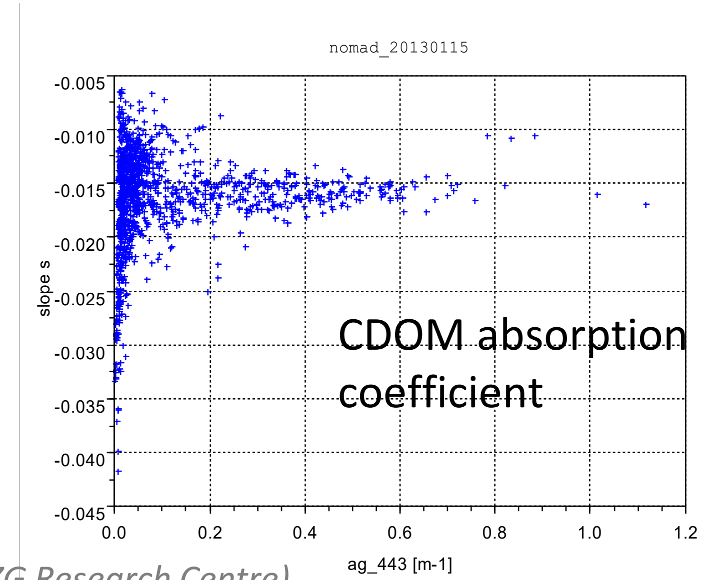
From R. Doerffer (Brockmann Consult & HZG Research Centre)

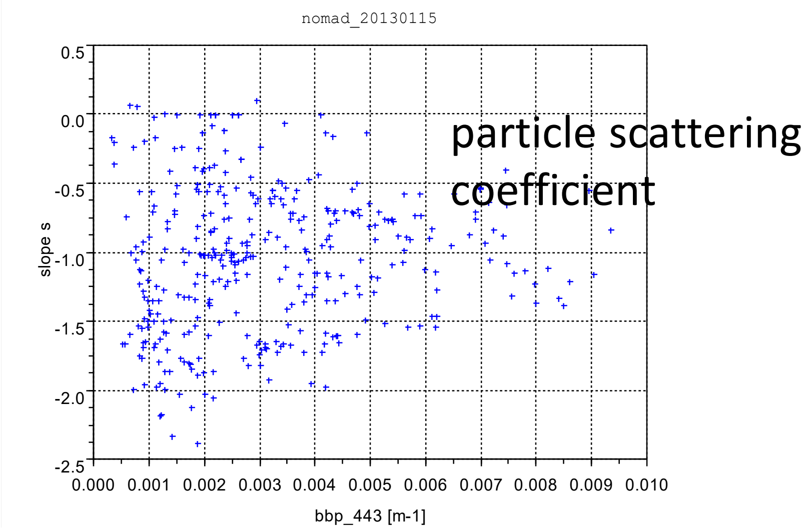
Natural Variabity and Covarianvce of Optical Properties

Relative absorption/ scattering from the NOMAD data set (NASA)





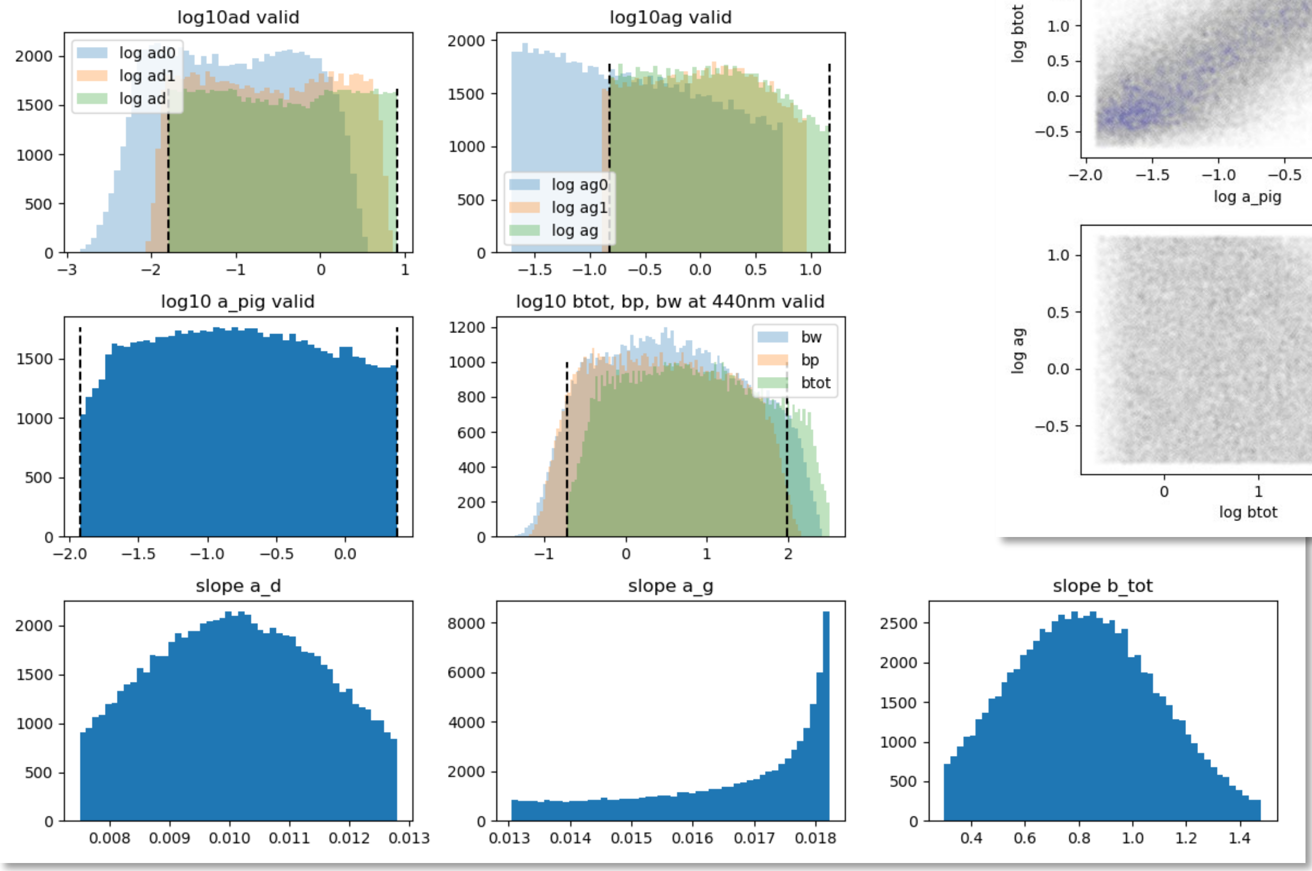


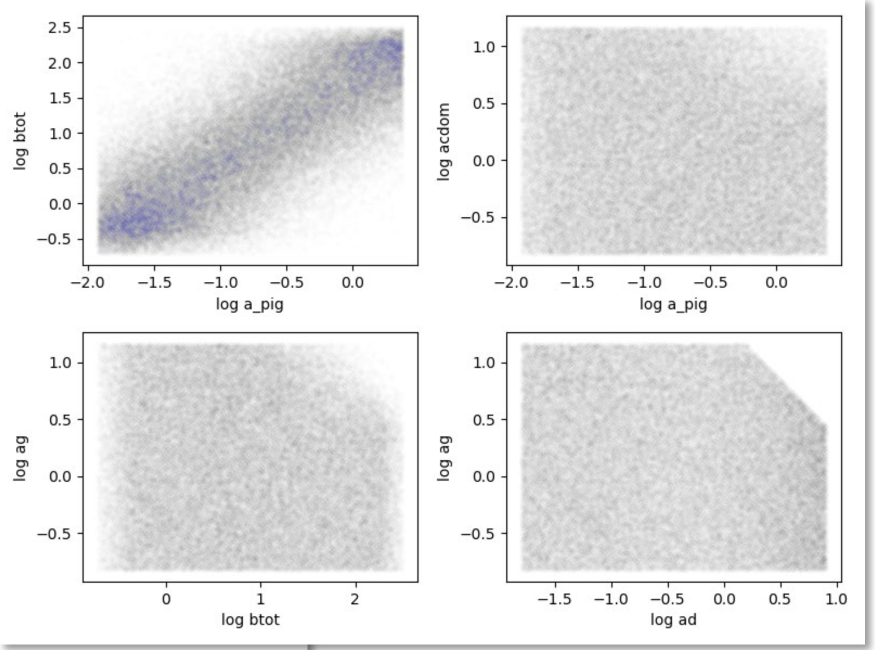


From R. Doerffer (Brockmann Consult & HZG Research Centre)

Training Dataset: Radiative Transfer Simulations

Distributions

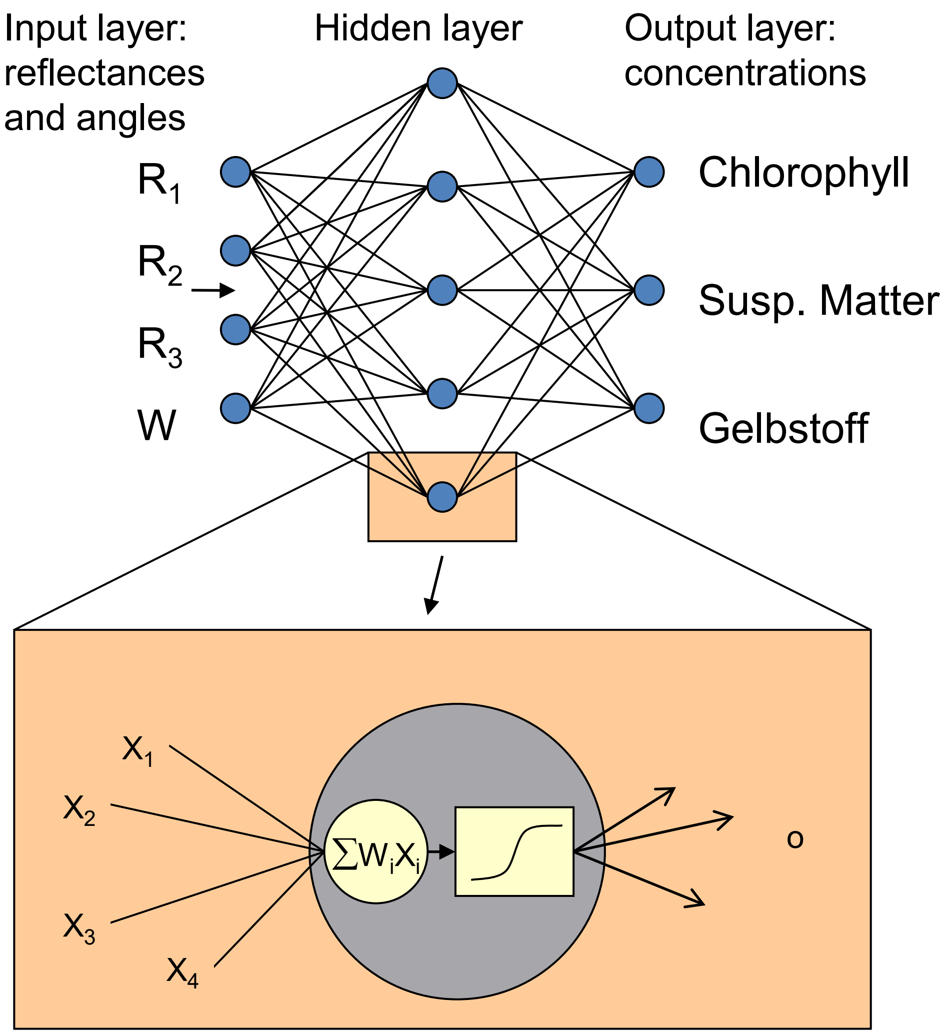




Covariances

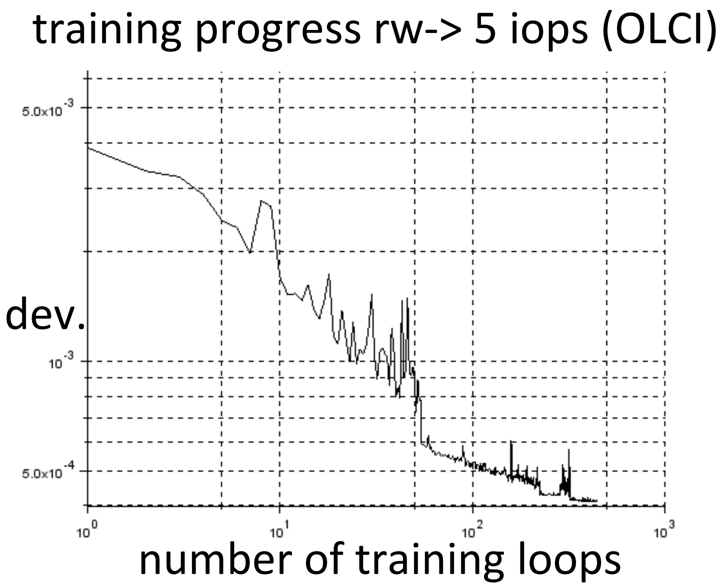
From D. Müller (Brockmann Consult, SeaLaBIO project)

Simplified scheme of MLP - NN



$$y_l = s(-d_l + \sum_{k=1}^{3} w_{kl} \cdot s(-c_k + \sum_{j=1}^{5} v_{jk} \cdot s(-b_j + \sum_{i=1}^{4} u_{ij} x_i)))$$

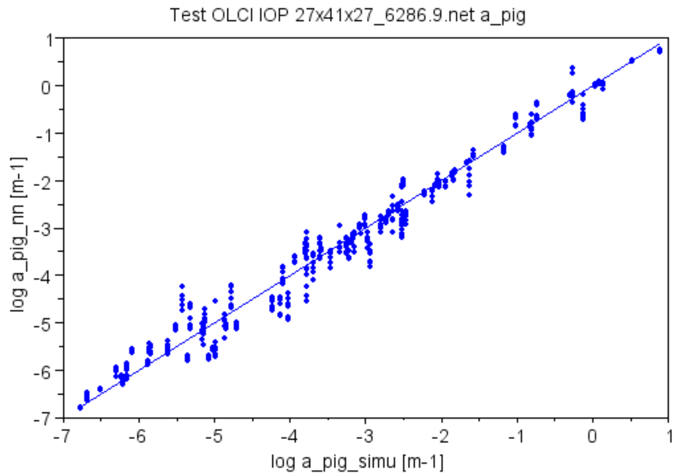
s: sigmoid function, u,v,w: weight, b,c,d: bias



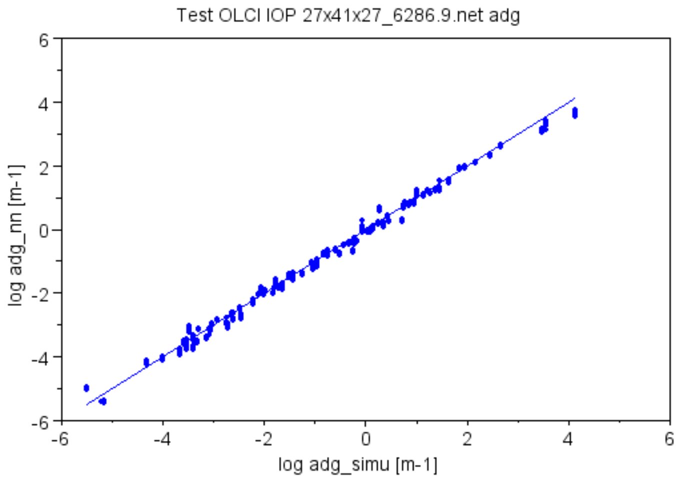
trainings samples: 1 350 882 points
test samples: 399 118 points
#planes=5: 17, 97, 77, 37, 5
average of residues:
training =0.000410 test =0.000413
ratio avg.train/avg.test=0.993550

From R. Doerffer (Brockmann Consult & HZG Research Centre)

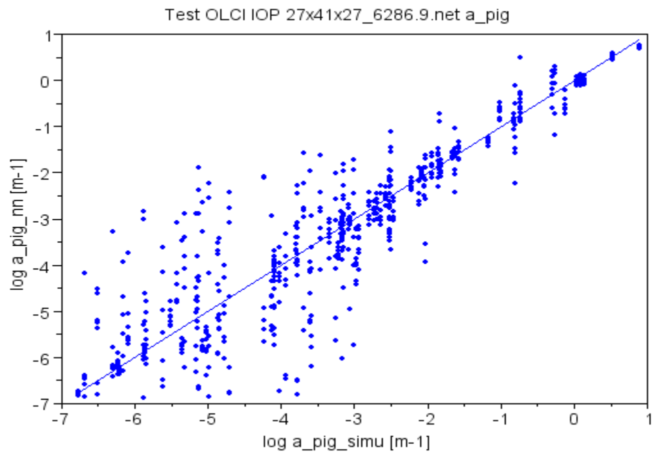
Training Performance / Sensitivity Tests of NNs



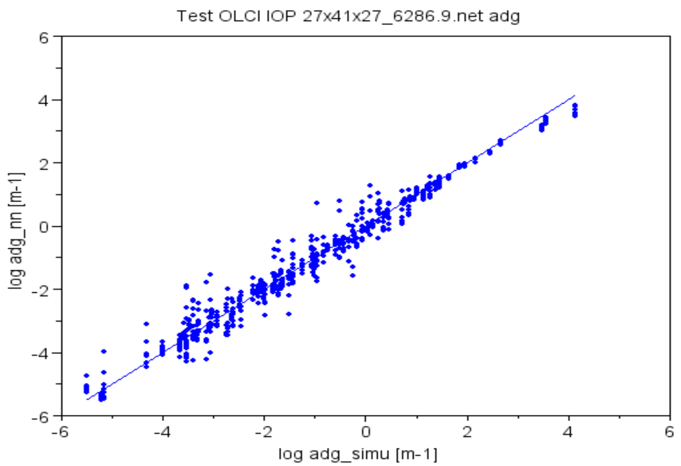
Test of a_pig, no additional error



Test of adg, no additional error



Test of a_pig with an extra random error with a standard deviation of 3%

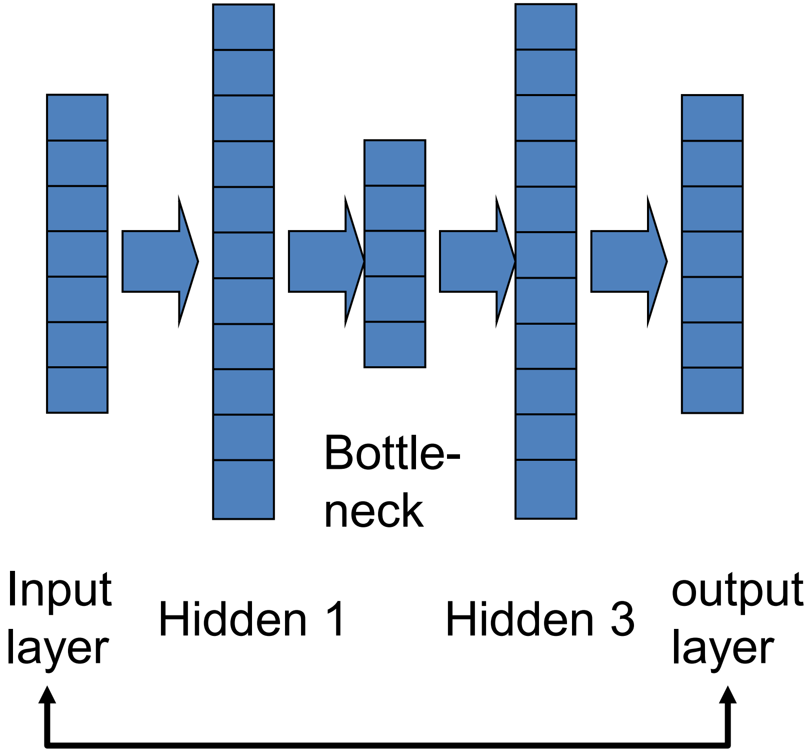


Test of adg with an extra random error with a standard deviation of 3%

From R. Doerffer (Brockmann Consult & HZG Research Centre)

Applicability Test („Out-of-Scope“)

- Important to detect toa radiance specta which are not in the simulated training data set
- These are out of scope of the atmospheric correction algorithm
- Autoassociative neural network with a bottle neck layer

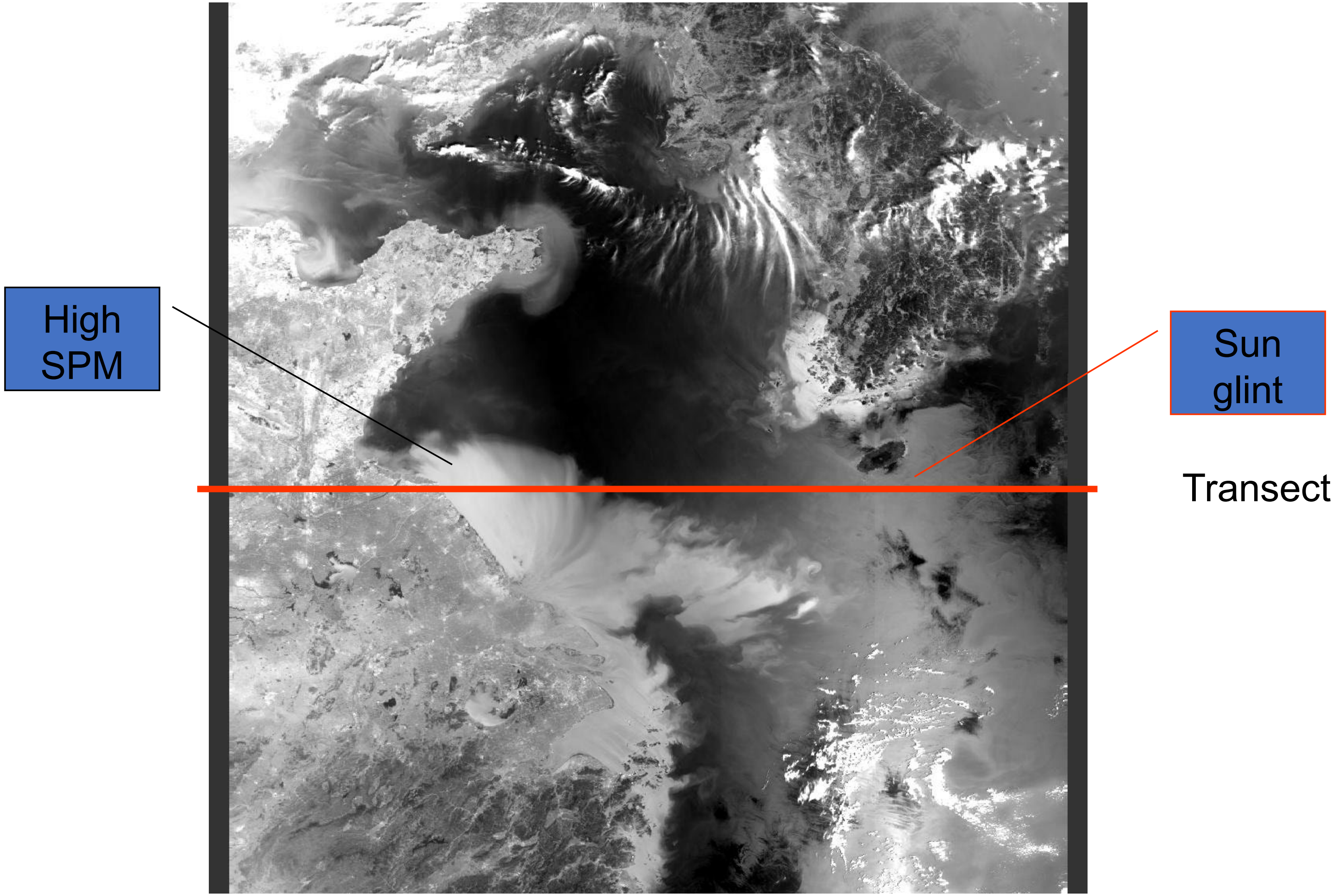


Functions also
as nonlinear PCA
i.e. bottle neck number of
neurons
Provide estimate of
Independent components

For the GAC training data
Set of ~ 1Mio. Cases
Bottleneck minimum was 4-5

From R. Doerffer (Brockmann Consult & HZG Research Centre)

OoS example



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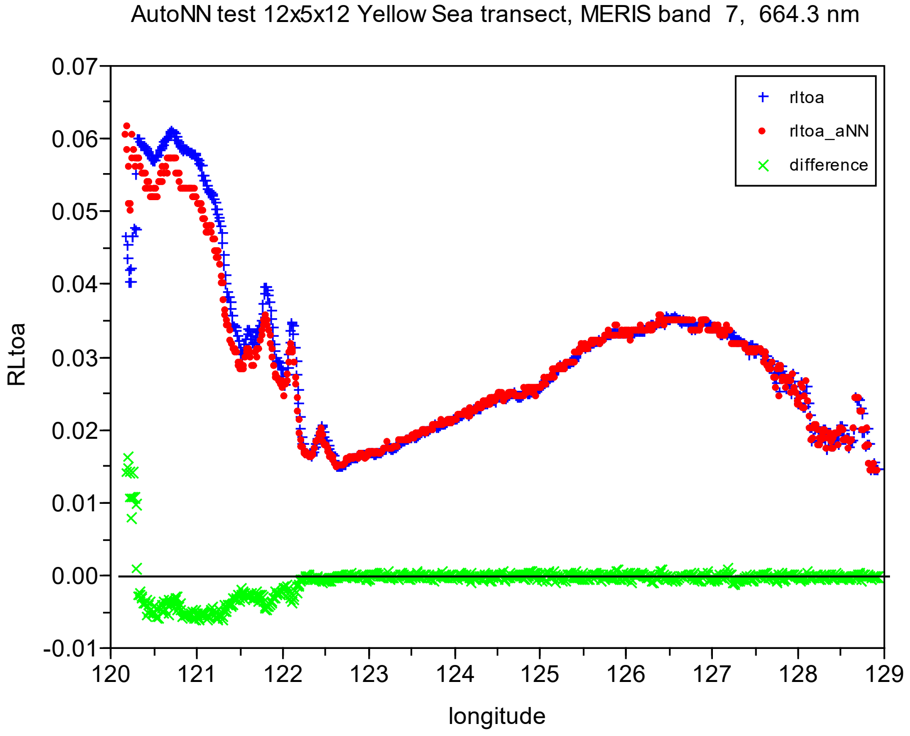
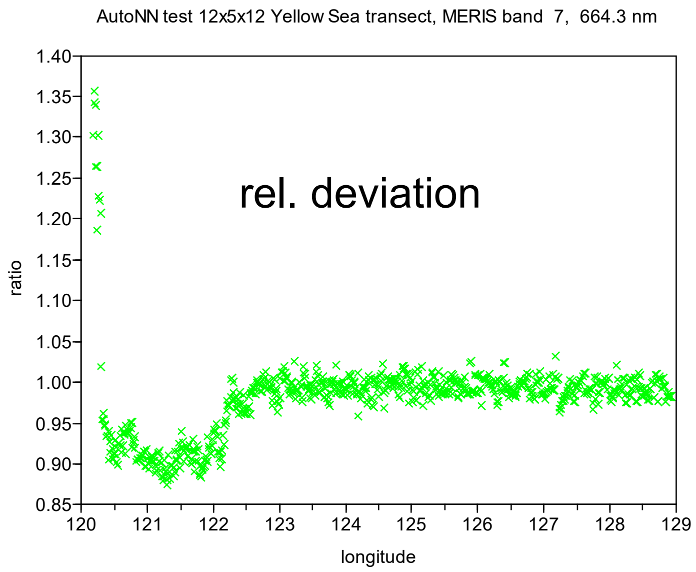
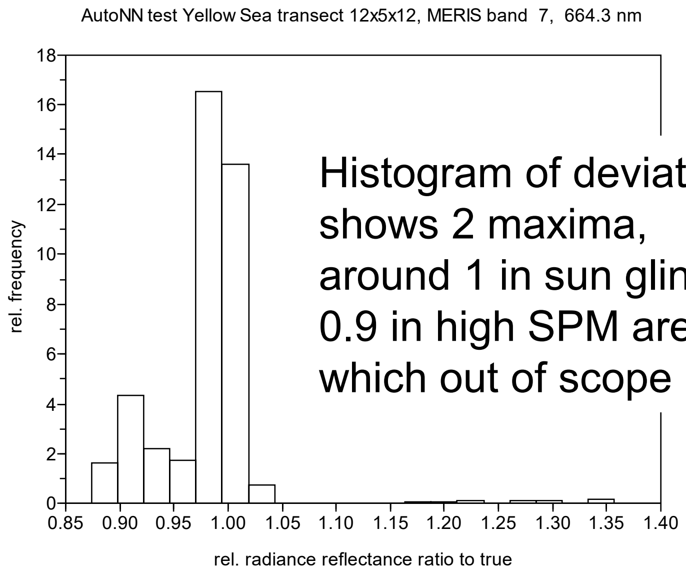
OoS example



significant deviation in area with high SPM concentrations, but not in sun glint area

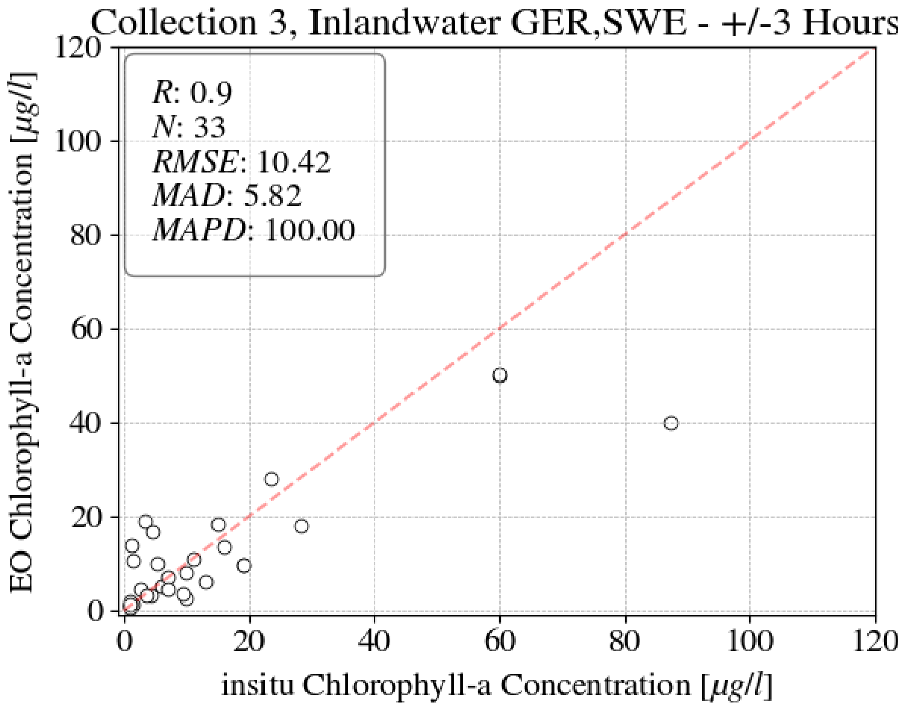


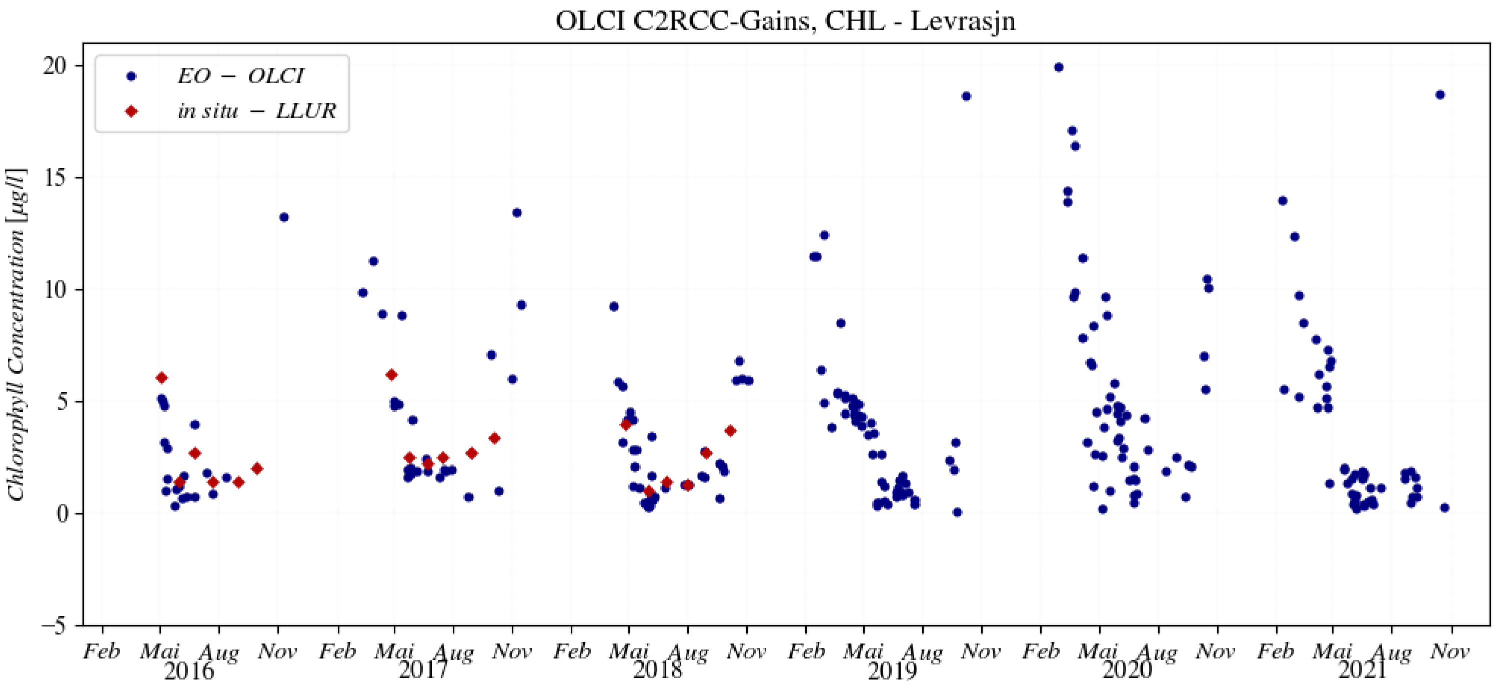


Histogram of deviations shows 2 maxima, around 1 in sun glint 0.9 in high SPM area, which out of scope

From R. Doerffer (Brockmann Consult & HZG Research Centre)

Validation with in-situ





From C. Lebreton (Brockmann Consult)

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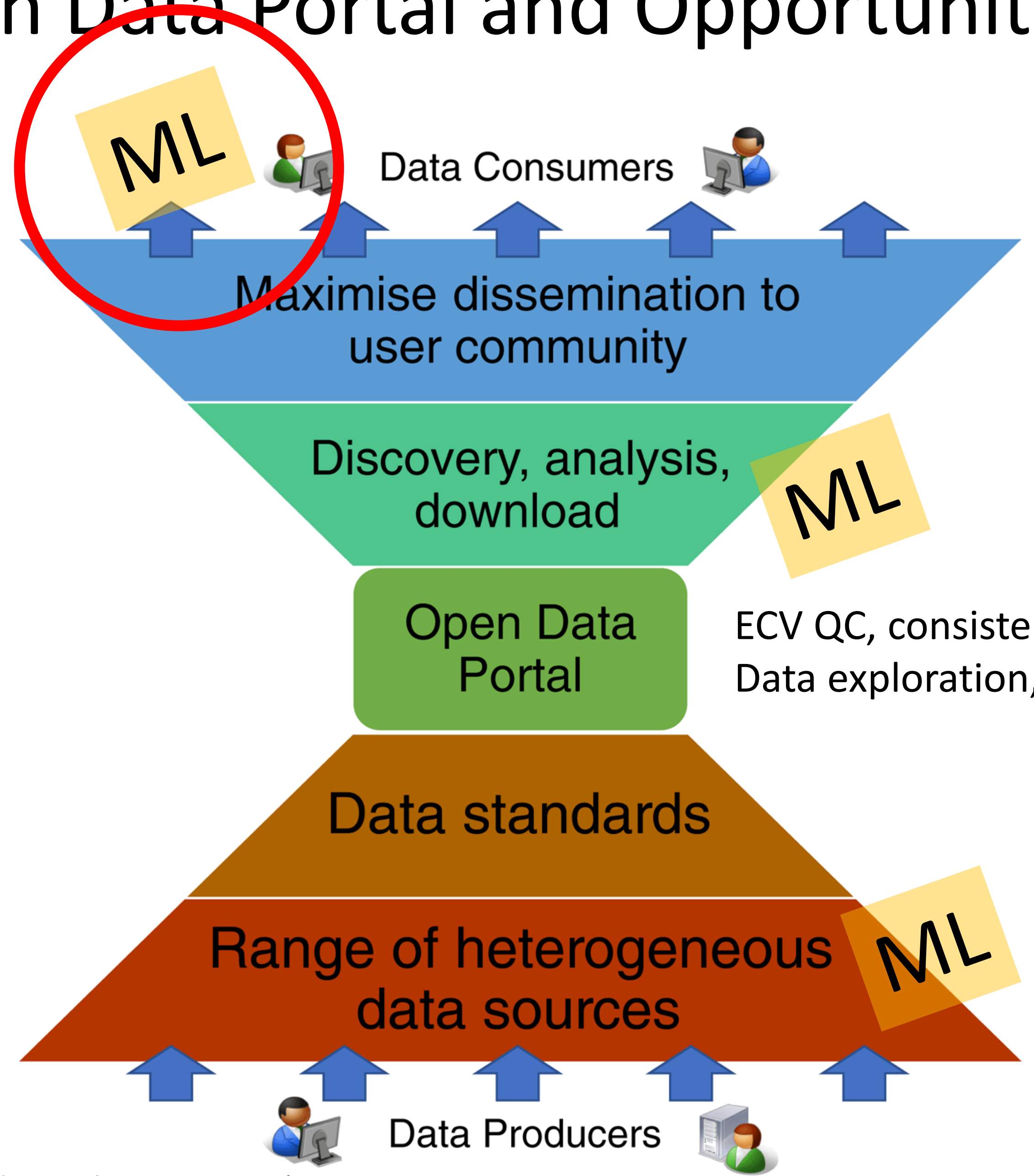

ECV QC, consistency
Data exploration, single and cross-CCI ECV analysis

ECV production
(L1 -> L2 -> L3 processing)

Adapted from P. Kershaw (CEDA, CCI Knowledge Exchange Project)

Knowledge Exchange Climate Change Initiative

AI Downstream From CCI ECV Production - Example.

Forecasting Environmental Cholera Risk in Coastal India

National Centre for Earth Observation

PML Plymouth Marine Laboratory

Estimated 2.9 million cases per year worldwide (WHO, 2017), 57% in Northern Indian Ocean countries

Vibrio cholerae (pathogenic bacteria responsible for cholera disease) found in coastal & estuarine waters

Established relationships between Essential Climate Variables (ECVs) and coastal distribution/ seasonal dynamics of *Vibrio cholerae*

AM Campbell[1], M-F Racault[2,3], S Goult[2,3], A. Laurenson[2], Cholera Risk: A Machine Learning Approach applied to Essential Climate Variables. *Submitted* to Int. J. Environ. Res. Public Health

[1]ESA Climate Office, [2]Plymouth Marine Laboratory, [3]National Centre for Earth Observation

Exploring potential of using multiple CCI-ECVs in a cross-ECV approach within a machine learning application to understand these complex relationships and forecast when outbreaks would occur

Study site: India coastal districts, monthly resolution, 2010-2018 based on cholera outbreak data availability

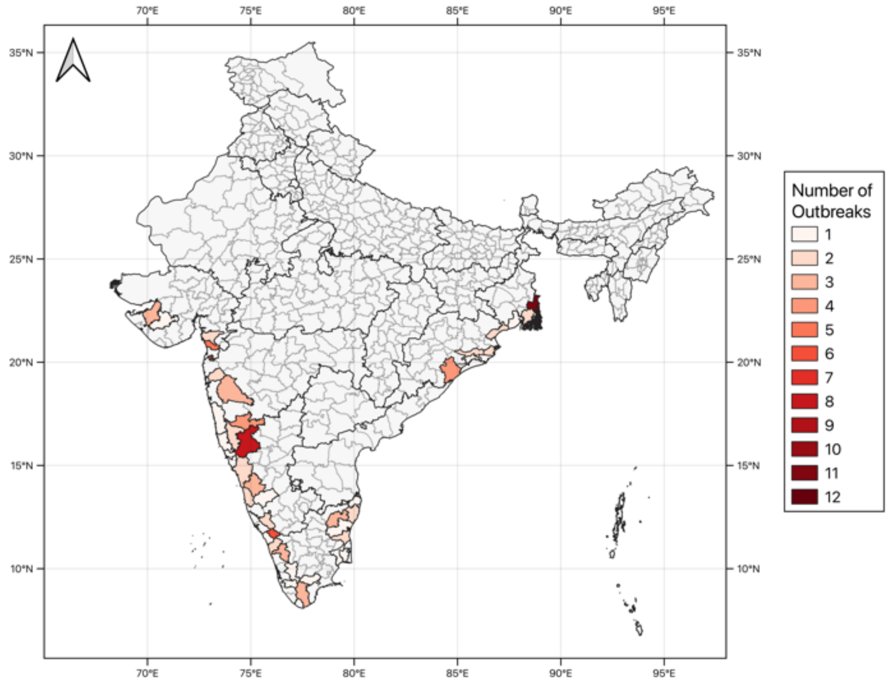

Figure 1: Cholera outbreaks recorded in coastal India districts within the study period 2010-2018

CCI ECV Datasets used – SST, Sea Surface Salinity, Ocean Colour, Sea Level, Soil Moisture, Land Surface Temperature.
With AVISO SLA, ERA Interim Precipitation, IDSP Cholera Outbreaks.

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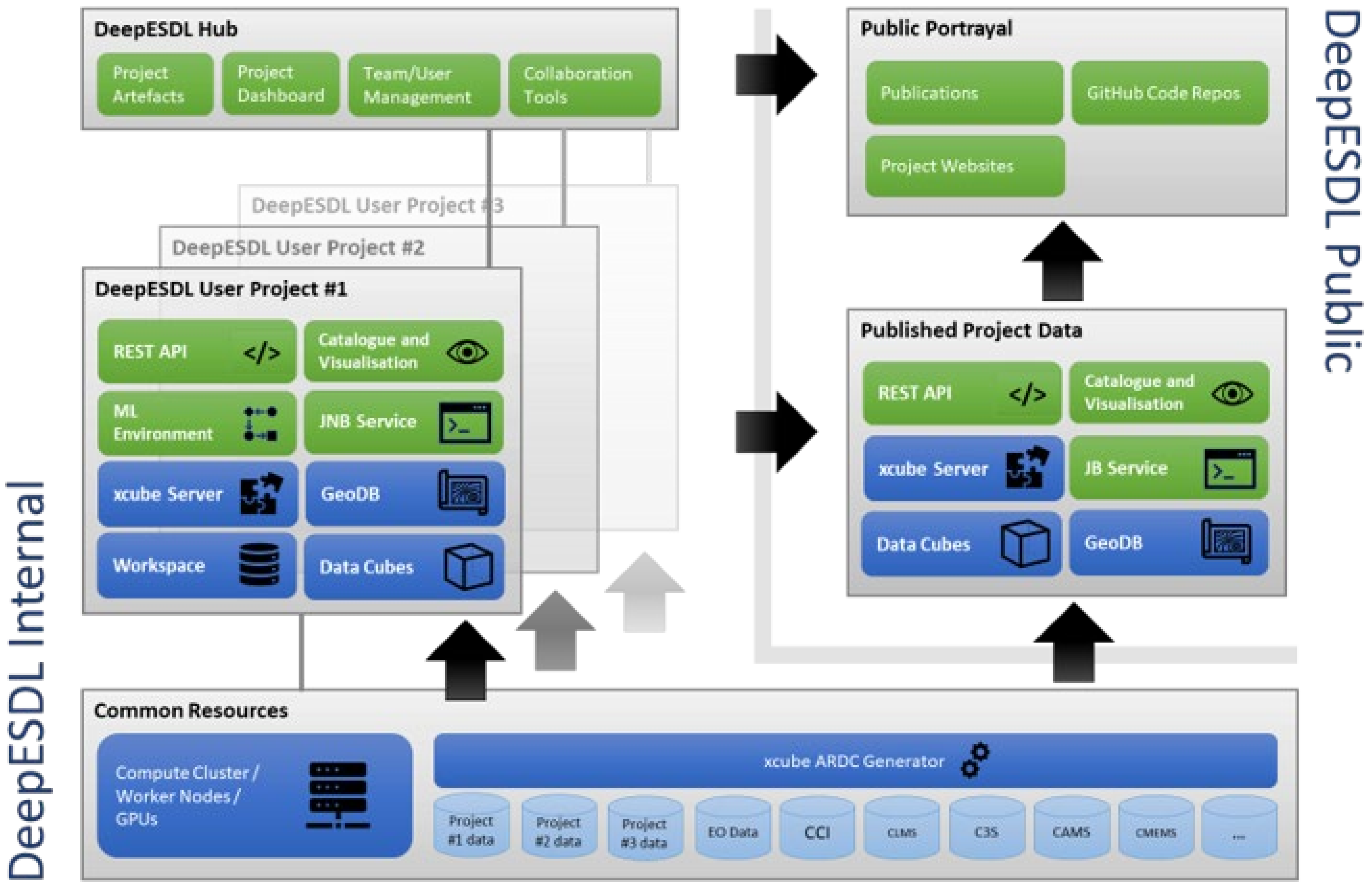
ESA Deep Earth System Data Lab

- Integrator of **Earth System and Climate data** from different ESA activities and other data owners into a single infrastructure.
- A **platform for collaborative research with focus on AI** allowing different scientists and teams to work collectively sharing data, tools and expertise.
- Support for **implementation and execution of individual projects** from ESA, particularly from the Science Clusters or from the scientific community.



Brockmann Consult GmbH — Prime Contractor, Technical Lead, Data Cube Ecosystem, Science User

Universität Leipzig — Science Lead, Dissemination, Outreach

EOX — ESDL Hub, User Tools

ScaDS.AI Dresden Leipzig — Scalable AI

Max Planck Institute for Biogeochemistry — Science User

earthwave — 4D Visualisation, Science user

Feature Selection and Anomaly Detection with the Cube

Russian Heat Wave 2010

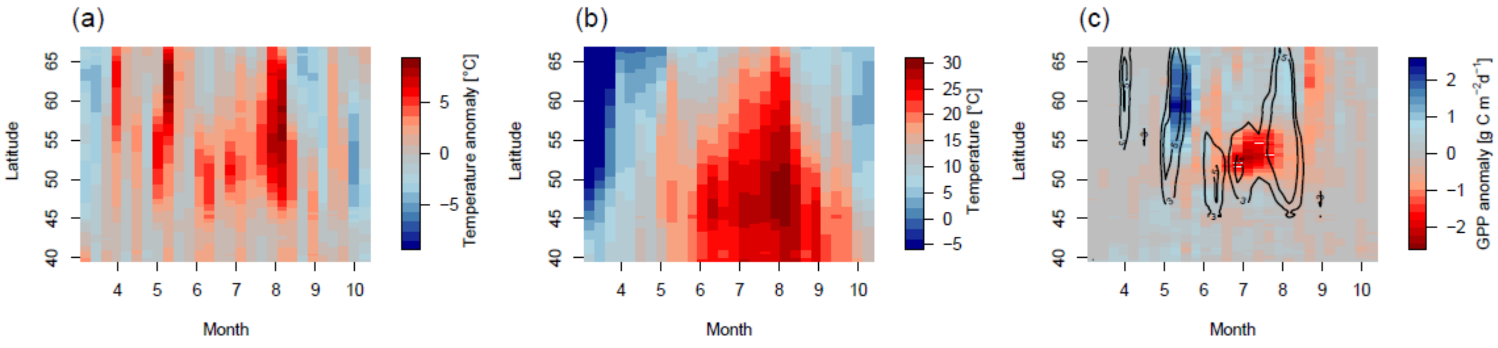


Figure 1. Longitudinal average (30.25 to 60.0° E) of (**a**) temperature anomalies (reference period: 2001–2011), (**b**) absolute temperature, and (**c**) GPP anomalies in 2010 with a contour of temperature anomalies (+3, +5 K).

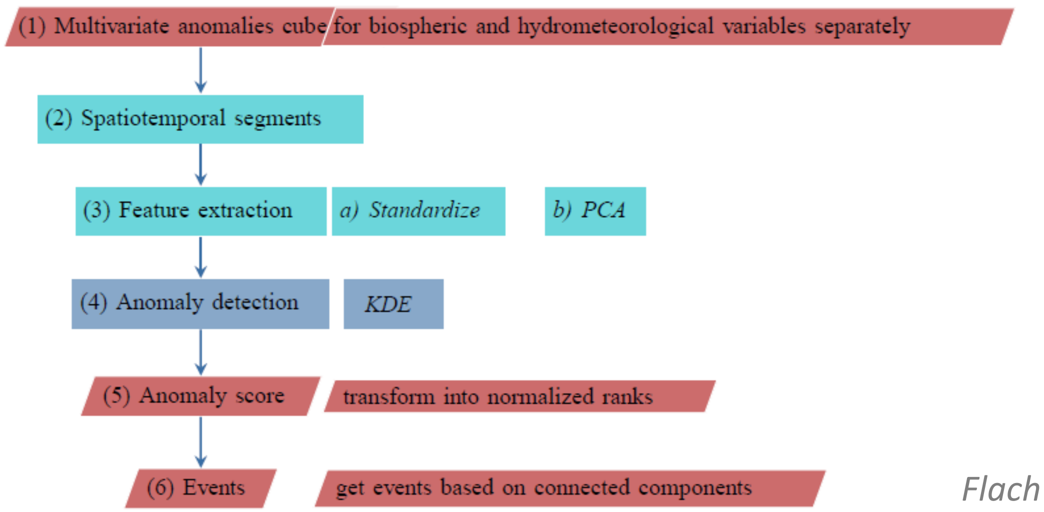


Figure 2. Data processing for detecting multivariate anomalies.

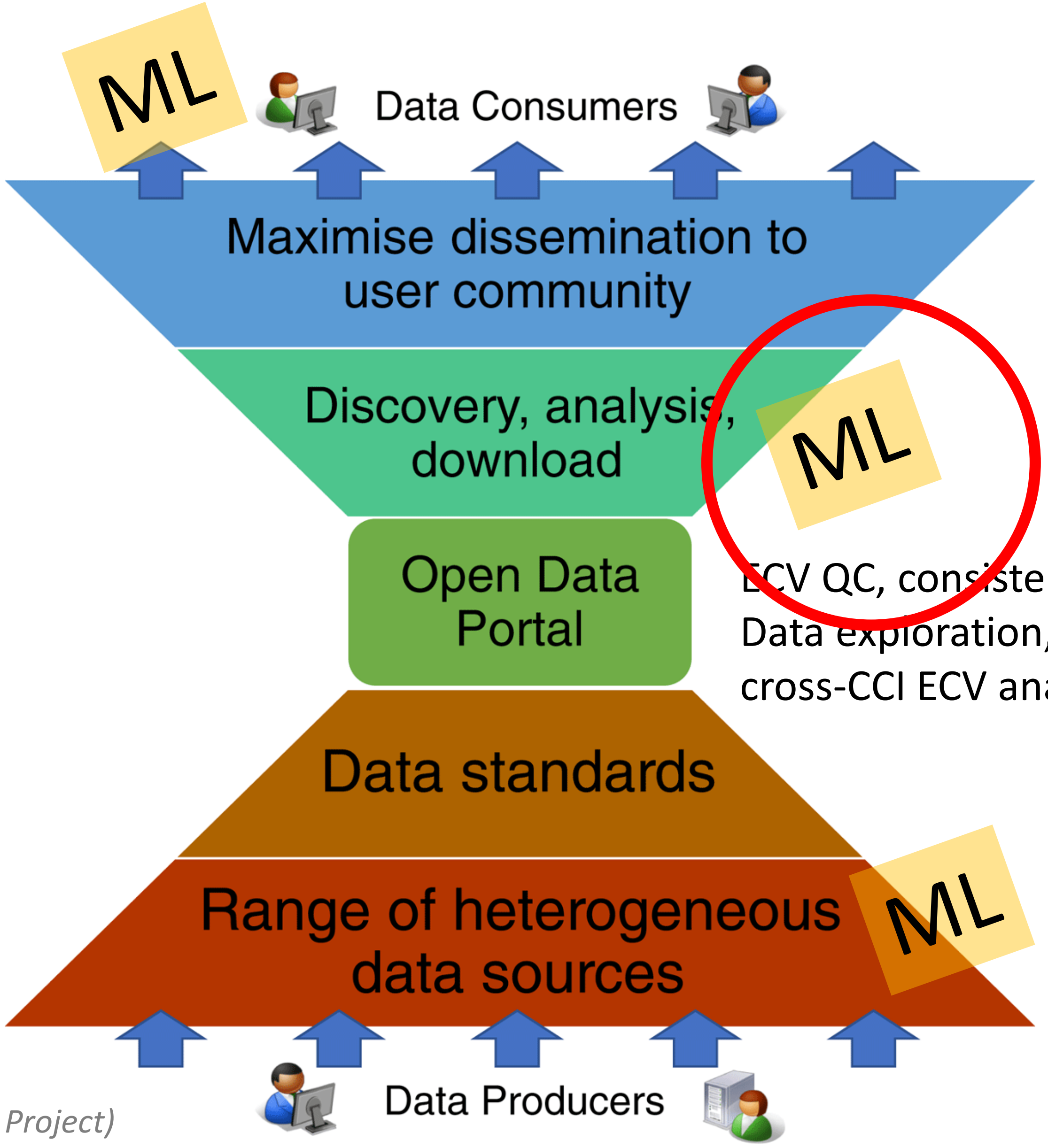
Flach et al, 2018: Contrasting biosphere responses to hydrometeorological extremes: revisiting the 2010 western Russian heatwave

What‘s next in CCI?

Machine learning to advance climate model evaluation and process understanding

A study performed by the ESA CCI Climate Modelling Group (CMUG).

Study will be undertaken by DLR and IUP (Univ. Bremen)



ECV QC, consistency
Data exploration, single and cross-CCI ECV analysis

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Adapted from P. Kershaw (CEDA, CCI Knowledge Exchange Project)

CCI CMUG: Machine learning to advance climate model evaluation and process understanding

Developing and applying machine learning (ML) techniques for advanced climate model evaluation and process understandingwith ESA CCI data

→ Creating enhanced ML-based observational products **from observations and climate models**

→ **Causal networks** derived from observations will be compared to those from state-of-the-art global climate models (CMIP6 and ICON model) to enhance process-oriented model evaluation with ESA CCI data

Can **cloud classes** be derived from ESA CCI CLOUD data with ma...hine learning to improve climate model evaluation?

How well does the **ICON** model reproduce the **observed me**... **variability of satellite derived cloud classes** (regime-orient...

Machine learning

What are the **causal relationships and networks** in the real world as derived from **ESA CCI data**?

Can the **ICON** climate model **reproduce** the **causal networks** between c... **properties and cloud controlling factors** as derived from ESA CCI data fo... cloud regimes? And for different **land cover types**?

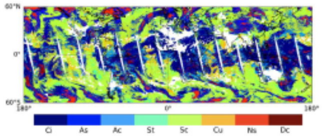
How well do **CMIP6** models reproduce the **observed variability** and (if detectable in the observations) **trends** in the historical record of **snow cover and permafrost**?

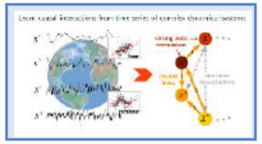
Can the addition of snow and permafrost to the **causal networks** in WP2 improve the analysis?

WP1
Enhancing observational products for climate model evaluation with machine learning

WP2
Causal model evaluation for cloud regimes and land cover types

WP3
Evaluation of CMIP6 models with the ESMValTool





ESMValTool
Earth System Model Evaluation Tool

Thank you for your attention

Carsten Brockmann, ESA CCI Knowledge Exchange Coordinator

http://climate.esa.int

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