



Retrieval of the diffuse attenuation coefficient $K_d(\lambda)$ in open and coastal waters using a neural network inversion

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Purpose of the study (1/2)

- Diffuse attenuation coefficient $K_d(\lambda)$ of the spectral downward irradiance plays a critical role:
 - Heat transfer in the upper ocean (Chang and Dickey, 2004; Lewis et al., 1990; Morel and Antoine, 1994)
 - Photosynthesis and other biological processes in the water column (Marra et al., 1995; McClain et al., 1996; Platt et al., 1988)
 - Turbidity of the oceanic and coastal waters (Jerlov, 1976; Kirk, 1986)

Purpose of the study (2/2)

- $K_d(\lambda)$ is an apparent optical property (Preisendorfer, 1976) → varies with solar zenith angle, sky and surface conditions, depth
- Satellite observations: only effective method to provide large-scale maps of $K_d(490)$ over basin and global scales
- Ocean color remote sensing: vertically averaged value of $K_d(490)$ in the surface mixed layer

State-of-the art (1/2)

- One Step Empirical relationships:

- NASA Meris algorithm (Werdell, 2009):

- $K_d(490) = 10^{(-0.8515 - 1.8263 X + 1.8714 X^2 - 2.4414 X^3 - 1.0690 X^4)} + 0.0166$

with $X = \log_{10}(R_{rs}(490)/R_{rs}(560))$

- Alternative algorithm (Kratzer, 2008)

- $K_d(490) = \exp(-1.03 * \log(R_{rs}(490)/R_{rs}(620)) - 0.18) + 0.0166;$

State-of-the art (2/2)

- Two-step empirical algorithm with intermediate link

– Morel, 2007:

- $\text{chl-a} = 10^{(0.4502748 - 3.259491 * X + 3.522731 * X^2 - 3.359422 * X^3 - 0.949586 * X^4)}$

with $X = \max(\text{Rrs}(443), \text{Rrs}(490), \text{Rrs}(510))$

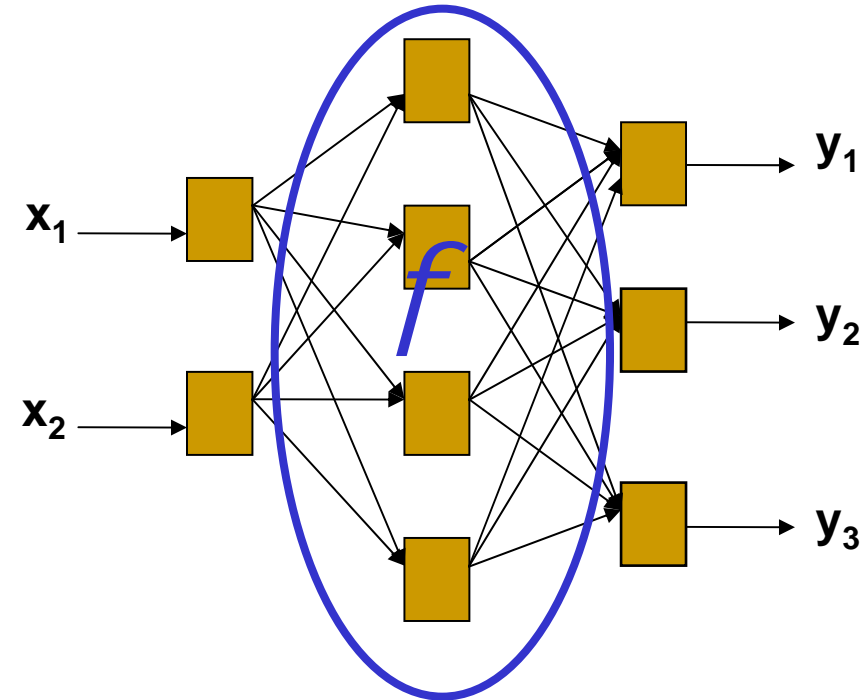
- $\text{Kd}(490) = 0.0166 + 0.07242[\text{chl-a}]^{0.68955}$

Way to improve the estimation

- Use of artificial neural networks → **Multi-Layer Perceptron (MLP)**
 - Purely empirical method
 - Non-linear inversion
 - Universal approximator of any derivable function
 - Can handle “easily” noise and outliers
 - Taking more spectral information
- **Method widely used in atmospheric sciences but rarely in spatial oceanography**

Principles of NN

- A MLP is a set of interconnected neurons that is able to solve complicated problems
- Each neuron receives from and send signals to only the neurons to which it is connected
- Applications in geophysics:
 - Non-linear regression and inversion (Badran and Thiria, J. Phys. IV, 1998; Cherkassky, Neural Networks, 2006)
 - Statistical analysis of dataset (Hsieh, W.W, Rev. Geophys., 2004)



Advantages:

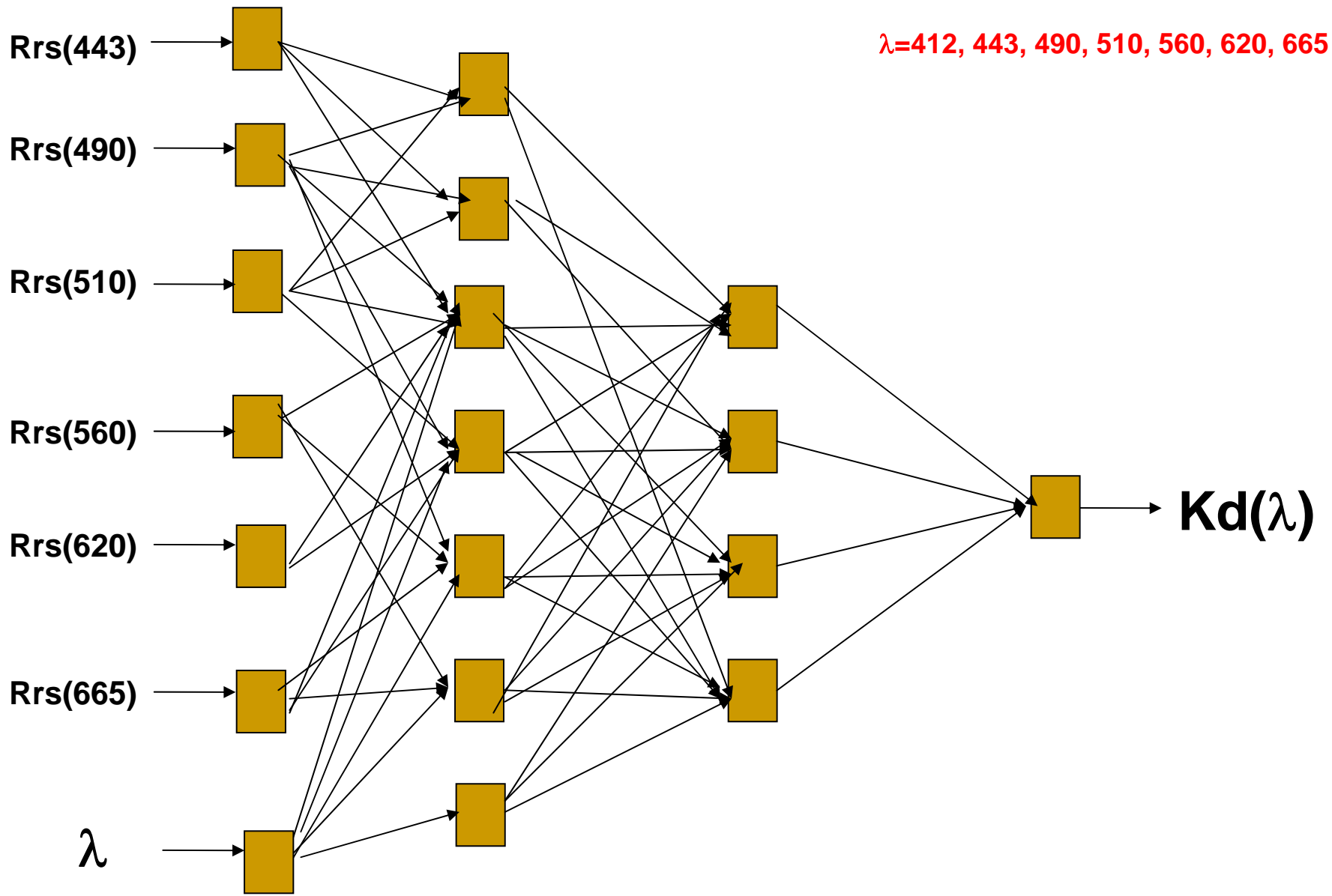
- Universal approximators of any non-linear continuous and derivable function
- Multi-dimensional function
- More accurate and faster in operational mode

Limits and drawbacks:

- Need adequate database
- Learning phase is time consuming
- Number of hidden layers and neurons unknown: need to determine them

Dataset

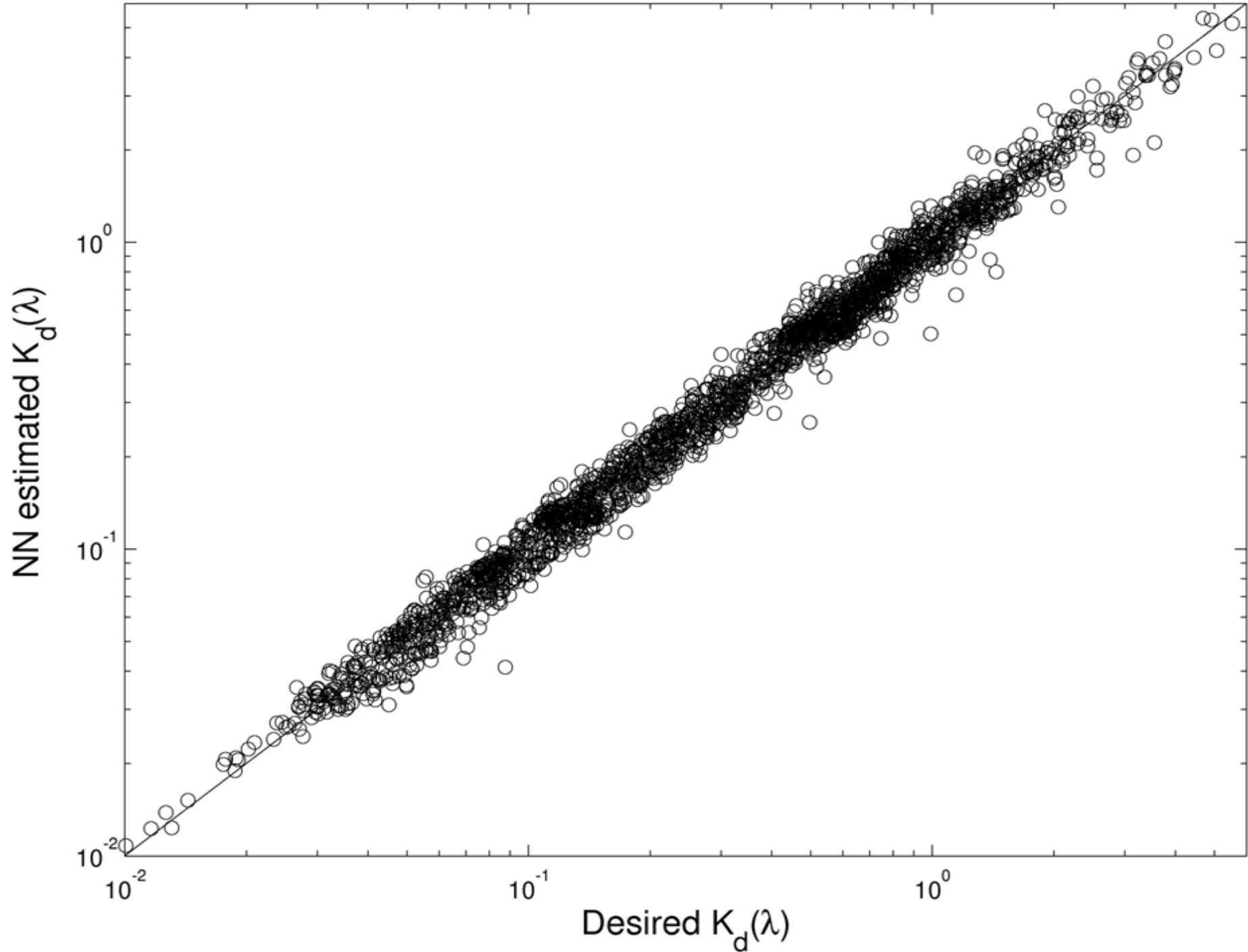
- Learning/testing datasets → Calibration of the NN
 - NOMAD database (Werdell and Bailey, 2005):
 - 337 set of $(R_{rs}, K_d(\lambda))$ per wavelength
 - IOCCG synthetic dataset (<http://ioccg.org/groups/lee.html>):
 - 1500 set of $(R_{rs}, K_d(\lambda))$ per wavelength
 - Three solar angles: 0° , 30° , 60°
- 80% of the entire dataset randomly taken for the learning phase (e.g., determination of the optimal configuration of the artificial neural networks)
- The rest of the dataset used for the validation phase



Architecture of the Multi-Layered Perceptron:
 Two hidden layers with 7 neurons on the first layer and 4 on the second layer

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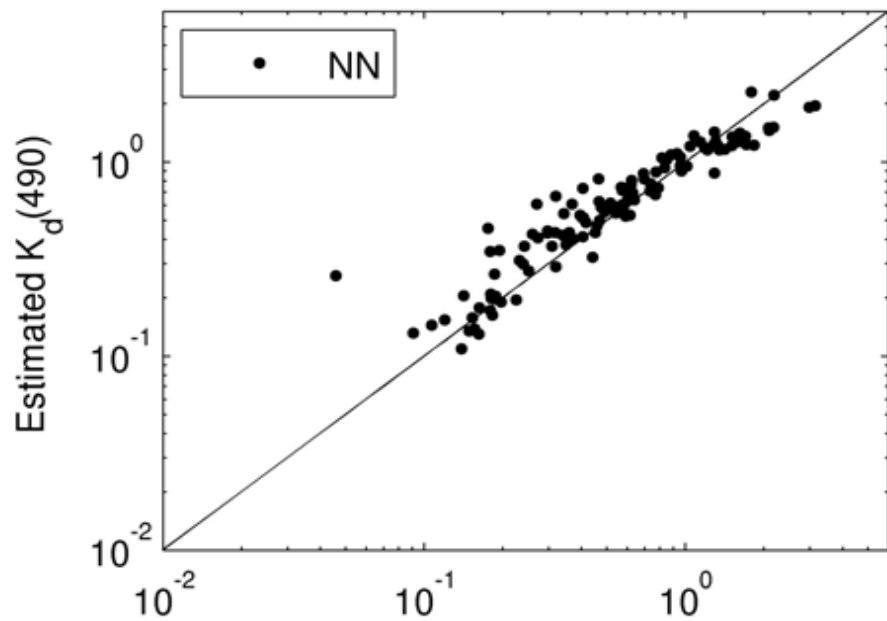
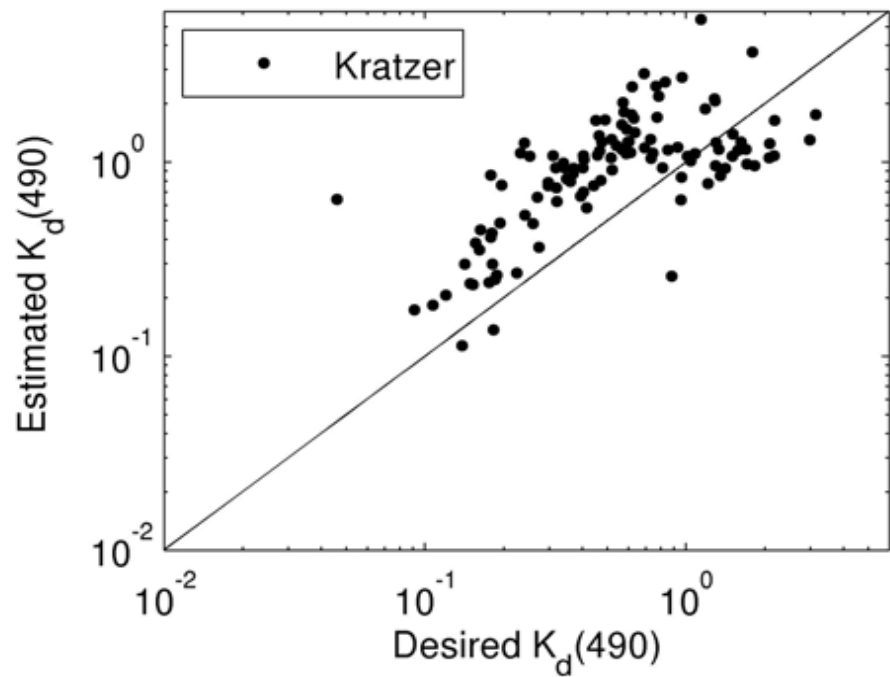
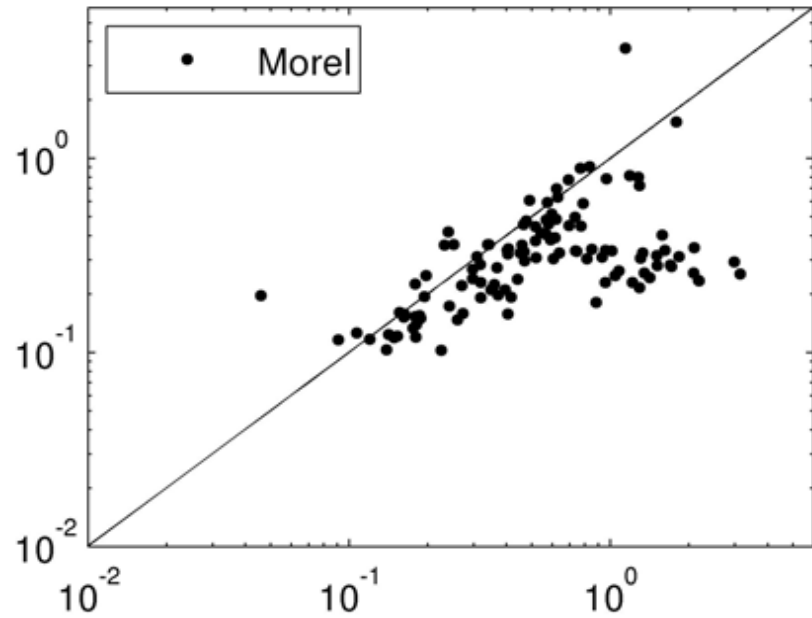
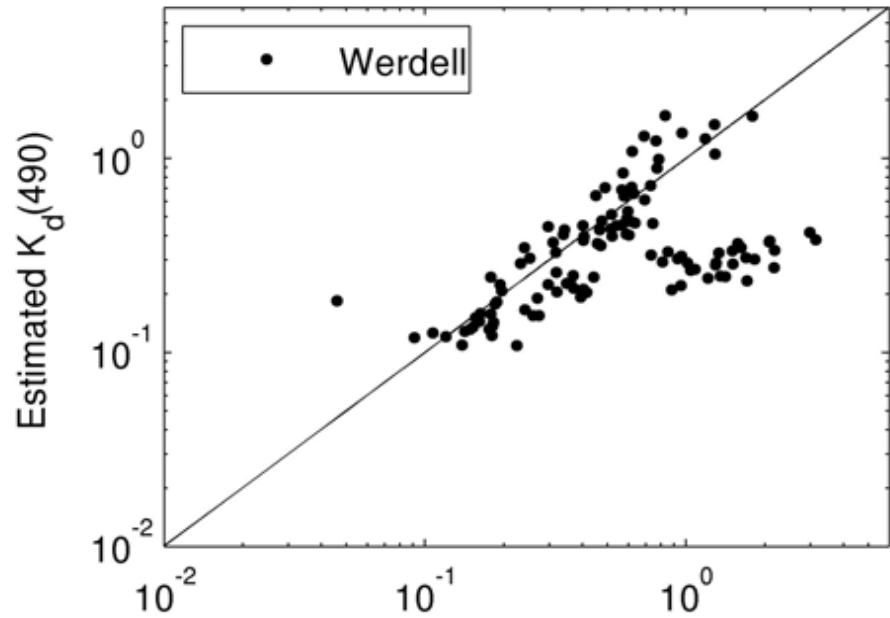


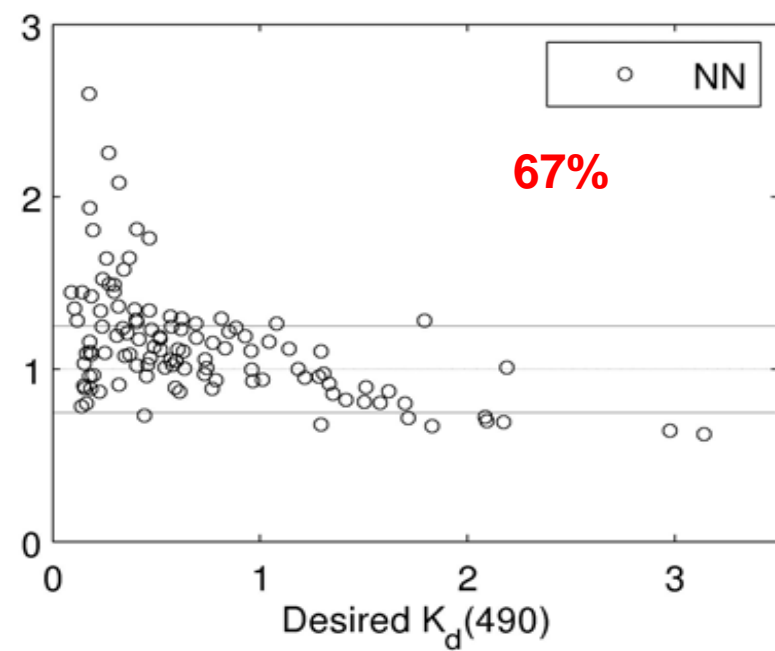
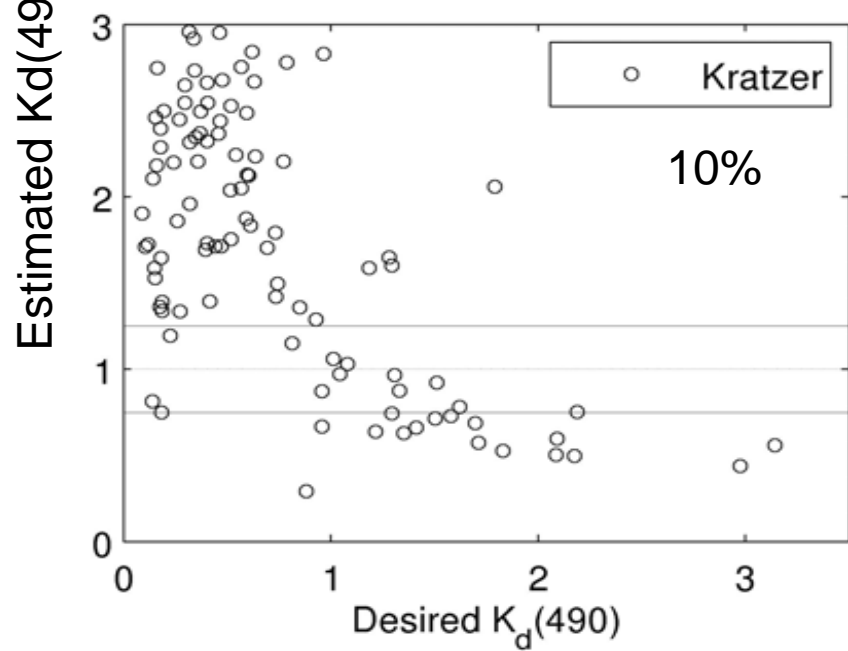
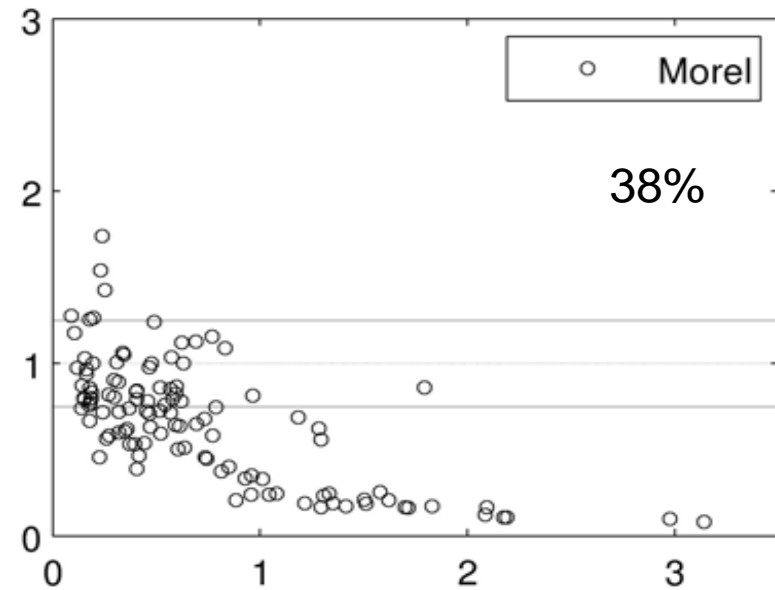
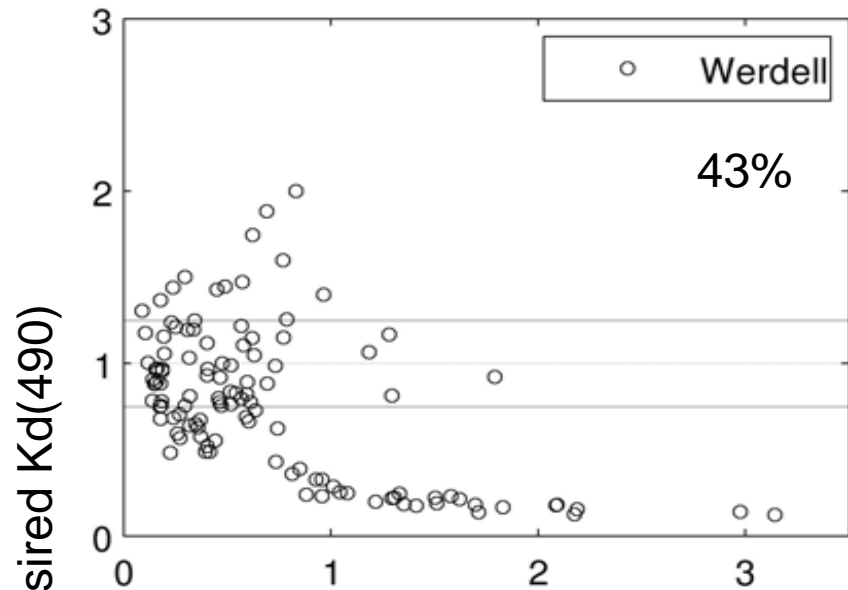
	RMS (m^{-1})	Relative error (%)	Slope	r
NN	0.110	10.09	1.0	0.98

Statistics on the test dataset

Comparison with other methods

- **COASTLOOC DATABASE (Babin et al., 2003)**
 - Observations in European coastal waters between 1997 and 1998
 - Entirely independent dataset from NOMAD and IOCCG
 - $K_d(490)$ ranging from 0.023 m^{-1} and 3.14 m^{-1} with a mean value of 0.64 m^{-1}
 - Nb total data: 132
- **Comparison of $K_d(490)$**





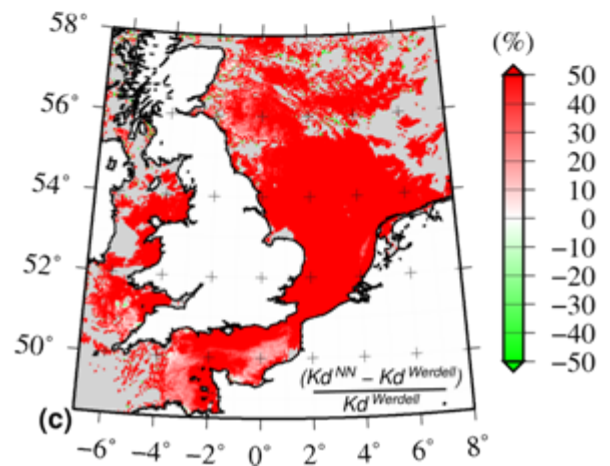
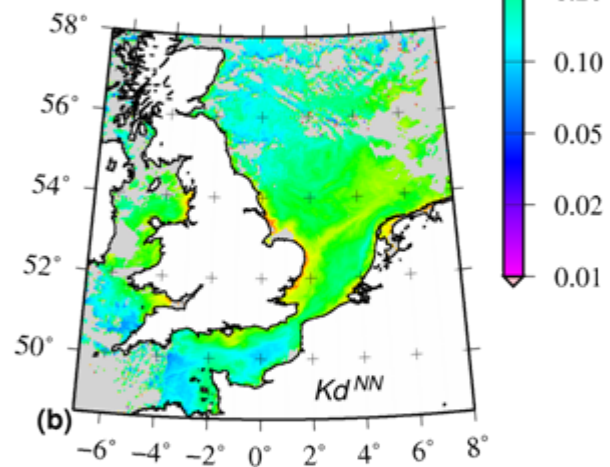
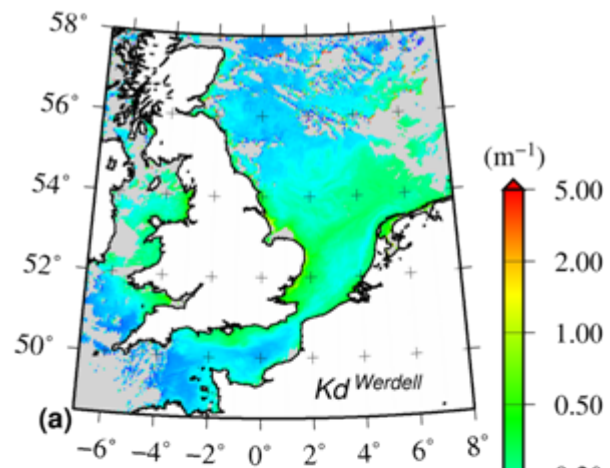
	<i>Werdell</i>	<i>Morel</i>	<i>Kratzer</i>	<i>NN</i>
RMS	1.204	0.732	0.846	0.212
Relative error (%)	48.81	43.17	124.48	25.23
Slope	0.24	0.12	0.49	0.79
Intercept	0.34	0.28	0.76	0.16
r	0.13	0.19	0.40	0.94

Conclusions and Perspectives

- On the used dataset:
 - Net overall improvement of the estimation of the $K_d(\lambda)$
 - Same quality for the very low values of $K_d(490)$, i.e. $< 0.2 \text{ m}^{-1}$
 - Huge improvement for the greater values, especially for very turbid waters ($K_d(490) > 0.5 \text{ m}^{-1}$)
- Will be freely available at:
 - <http://log.univ-littoral.fr/oceano/>

<i>SeaWiFS</i>	<i>412</i>	<i>443</i>	<i>510</i>	<i>555</i>	<i>670</i>
RMS	0.379	0.249	0.227	0.196	0.206
Relative error (%)	31.57	26.08	31.87	22.34	15.70
Slope	1.02	0.88	0.68	0.64	0.67
Intercept	0.15	0.18	0.16	0.12	0.29
r	0.95	0.95	0.95	0.94	0.87

Statistical results for a SeaWiFS Kd from COASTLOOC database



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