From species characteristics to ecosystem functions: a trait-based distribution model for upscaling the macrobenthos role in benthic-pelagic coupling over the Black Sea continental shelf

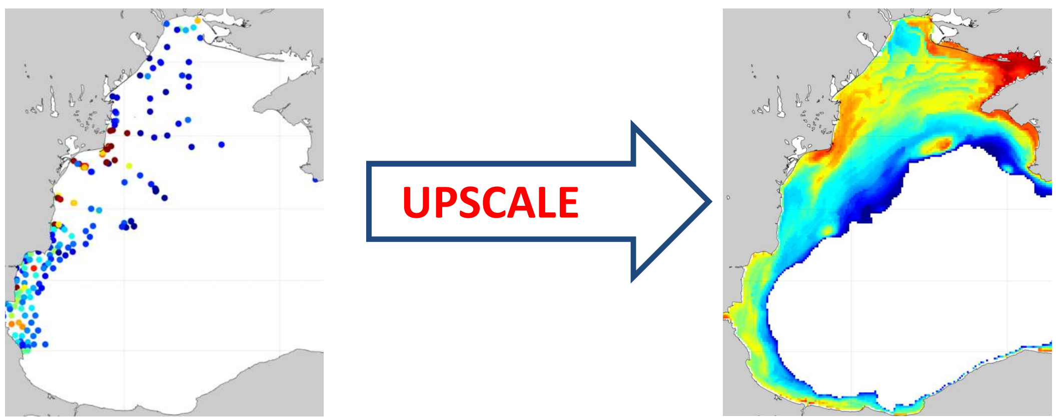
Marilaure Grégoire [1], Arthur Capet [1], Lei Chou[2], Nathalie Fagel [3], Evgeny Ivanov[1], Molly Lepoint [1], Catherine Meulders[1], Audrey Plante [2], Karline Soetaert [4], Adrian Teaca [5] Luc Vandenbulcke[1]

1. *MAST-FOCUS, Liege University, Belgium*
2. *Chemical Oceanography and Water Geochemistry,University of Brussels, Belgium*
3. *Laboratoire de géochimie des argiles, Liege University, Belgium*
4. *NIOZ, The Netherlands*
5. *GeoEcoMar, Romania*

The 52nd Ocean Liege Colloquium, May 17th – 21st 2021

Objective

Upscaling ecosystem functions

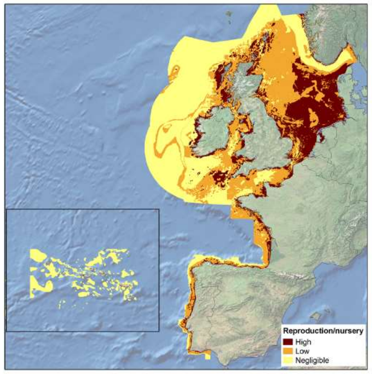


Species (traits) | **Ecosystem Funciton (traits maps)**

Field experiments | **Scales of management**

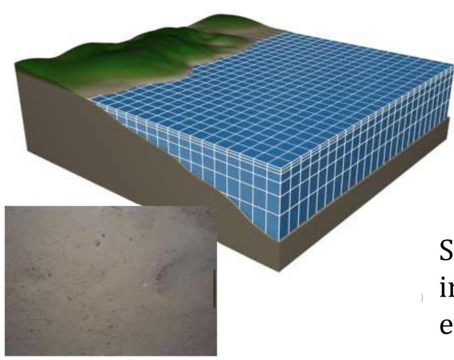
Why?

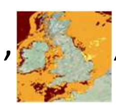
Mapping indicators and ecosystem functions

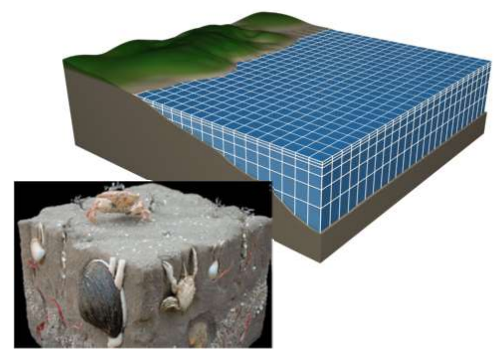


Integrating ecosystem functions into ocean models

Parameterization of ocean models that considers the characteristics and variability of the benthos



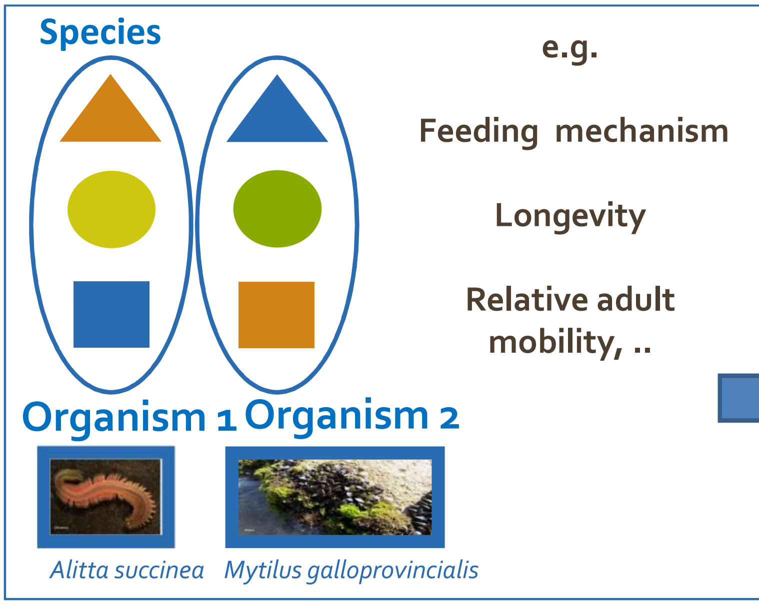
Parameterization [ ,  , ...]



Sediment mixing length, diffusion coefficient, injection pocket, pumping rate, roughness, erodability, filtration, biodeposition, ...

How?

Traits Distributions Models (TDMs)



TRAITS →

SPECIES ↓

Biological Traits / Species	Feeding mechanisms			Adult Longevity			Relative Adult Mobility			
	SF	DF	GB	<2	2-5	>5	None	Low	Medium	High
Mya arenaria	2	1	0	0	1	3	0	3	0	0
Mytilius galloprovincialis	3	0	0	0	1	3	3	1	0	0
Nereis rava	0	0	3	3	0	0	0	0	1	2
Terebellides stroemii	0	3	0	0	0	3	3	1	0	0
Lagis koreni	0	3	0	3	1	0	2	1	0	0
...										

Southwood hypothesis (1977) : *"The habitat provides the templet on which evolution forges characteristic life history strategy. This means that **biological traits can be related to the physical and biogeochemical properties of the environment**".*

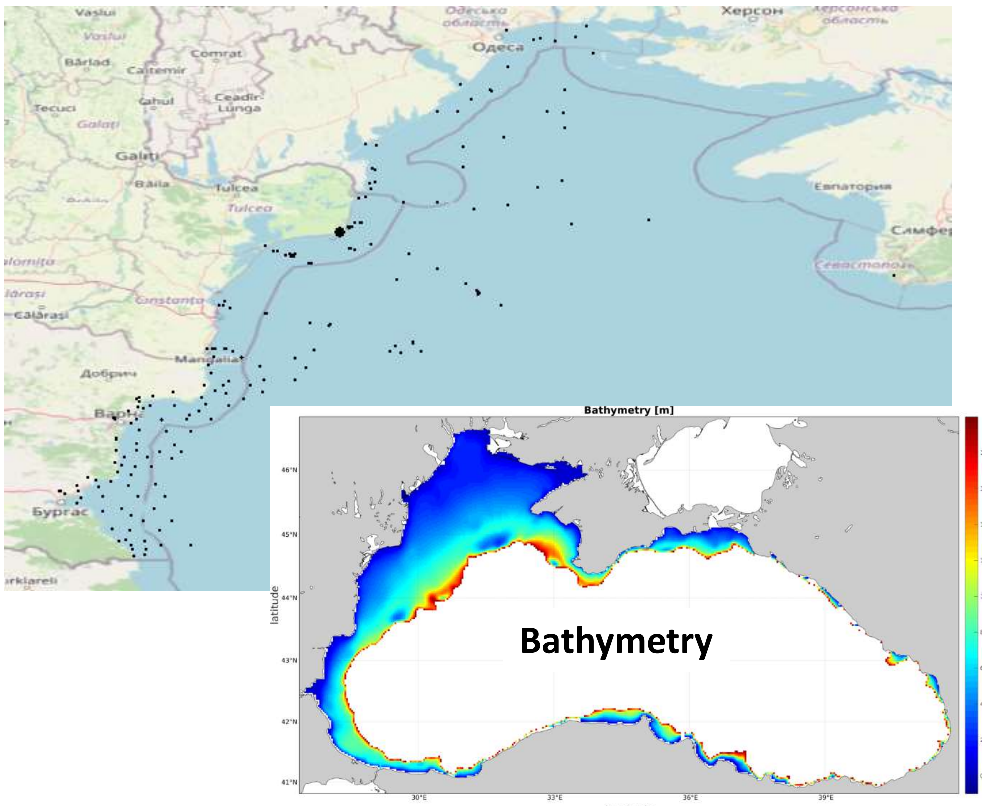
Selected Traits

- **Method of sediments reworking**
- **Propensity to move through the sediment**
- **Feeding mechanisms**
- **Burrow Type**
- **Max sediment dwelling depth**
- Degree of attachment
- Relative adult mobility
- Adult life habit
- Larval development mechanisms
- Propagule dispersal
- Larval type
- Longevity
- Maximum adult size
- Tolerance to disturbance

} Traits linked with the bioturbating activity of a species. (first five traits)

Macrobenthos data set in the Black Sea

237 stations (1995-2017)

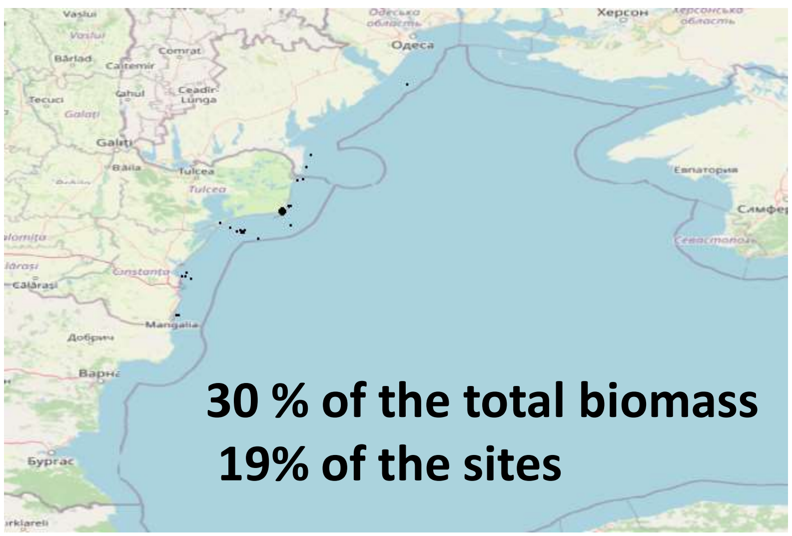


64 dominant species

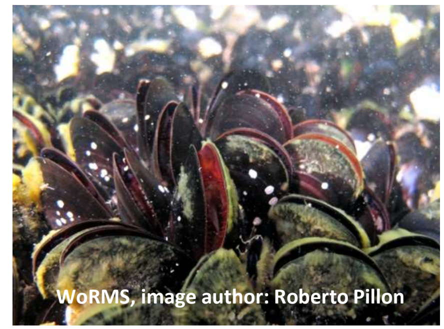
Phyllum	Class	# species	% of total Biomass
Mollusca	**Bivalvia, Gastropoda**	**32**	**80**
Annelida	**Polychaeta**	**19**	**17**
Crustacea	Malacostraca	4	1
Cnidaria	Anthozoa, Hydrozoa	3	<1
Tunicata	Ascidiacea	3	<1
Echinozoa	Holothuroidea	1	<1
Nemertea indet.			<1
Porifera	Demospongiae	1	<1

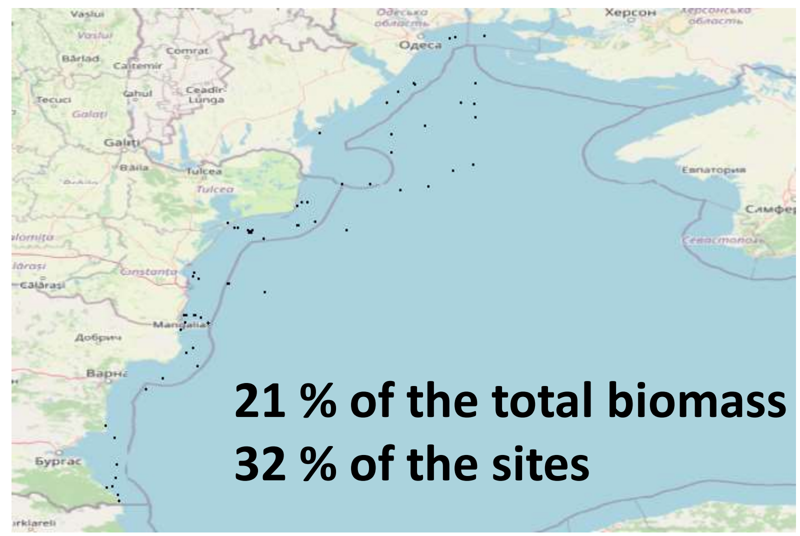
Dominant Species in terms of biomass

Mya arenaria Linnaeus, 1758



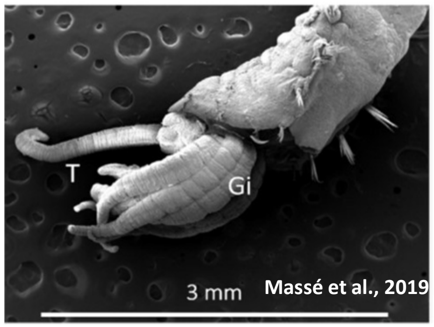
Mytilus galloprovincialis Lamarck, 1819

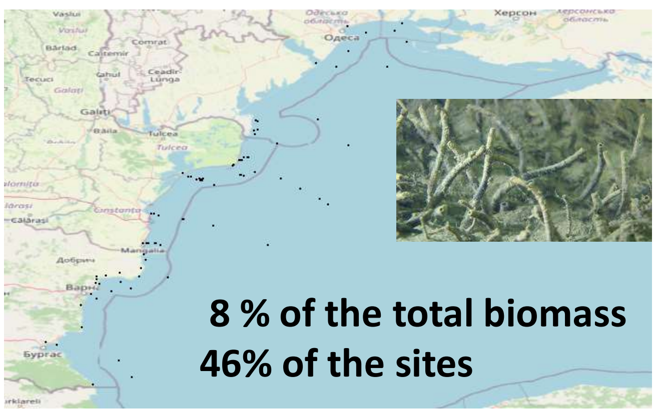




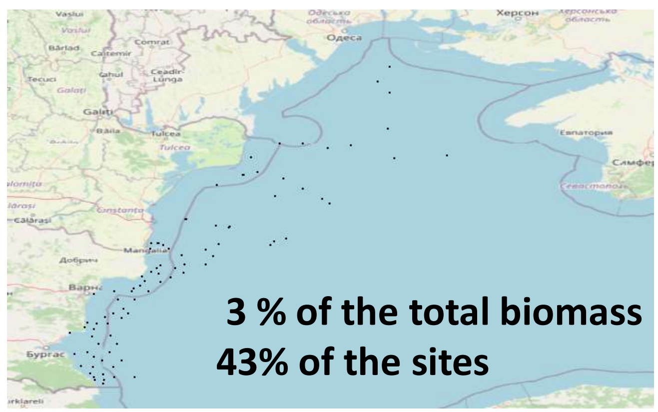
Dominant Species in terms of coverage

Melinna palmata Grube, 1870

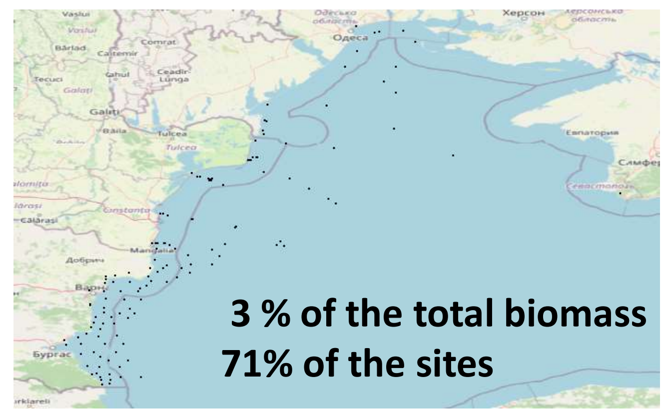




Terebellides stroemii Sars, 1835



Nephtys hombergii Savigny in Lamarck, 1818



Bioturbation Potential (BPc)

TRAIT	Modalities
Method of sediments reworking **(Reworking mode: Ri)**	(1) Epifauna that bioturbate at the sediment-water interface, (2) surficial modifiers (<1-2cm) (3) upward/downward conveyors that actively transport sediment to/from the sediment surface (4) biodiffusors
Propensity to move through the sedimentary matrix **(Mobility :Mi)**	(1) in a fixed tube (2) limited movement, sessile, but not in a tube (3) slow movement (4) free movement via burrow system

$$\boldsymbol{BP_c = \sum_{i=1}^{n} BP_i = \sum_{i=1}^{n} \sqrt{\frac{B_i}{A_i}}\, A_i\, M_i R_i}$$

$\boldsymbol{BP_c}$: Bioturbation potential of the community

$\boldsymbol{BP_i}$: per capita effect of **each species**

(Solan et al., 2004).

Irrigation Potential (IPc)

TRAIT	Modalities
Burrow Type **(BTi)**	(1) Epifauna, internal irrigiation (e.g. siphons) (2) Open irrigation (e.g. U- or Y-shaped burrows) (3) Blind ended irrigation (e.g. blind ended burrows, no burrow systems)
Feeding type **(FTi)**	(1) Surface filter feeder (2) Predator (3) Deposit feeder (4) Sub surface filter feeder
Injection pocket depth **(IDi)**	(1) 0 – 2 cm (2) 2 – 5 cm (3) 5– 10 cm (4) > 10 cm

$$IP_c = \sum_{i=1}^{n} IP_i = \sum_{i=1}^{n} \frac{B_i}{A_i}^{0.75} A_i \ BT_i \ FT_i \ ID_i$$

IP_c : Irrigation potential of the community

IP_i : per capita effect of **each species**

(Wrede et al., 2018).

Environmental variables

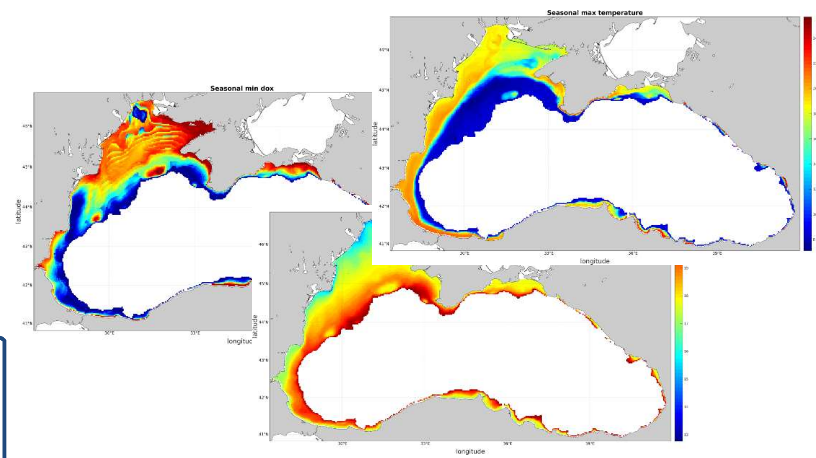
Black Sea operational model
3 km resolution run by ULiège

In-situ data: substrate (Folk 7 classification)

Model variables

Physical variables:
- Température,
- Salinity,
- Total shear stress (current+wave)

Biogeochemical variables
- Oxygen
- Flux of POC to the bottom
- Carbon in the sediment (two pools)
- PAR

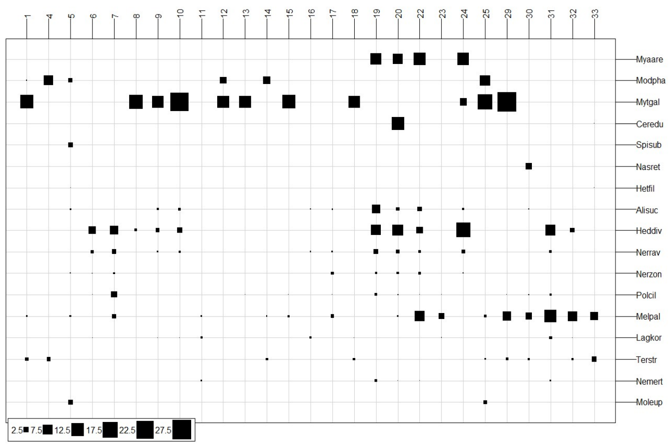


Average, std, min, max bottom values computed at seasonal and annual scale.

Species-Traits-Environment

STATIONS

SPECIES



R

TRAITS

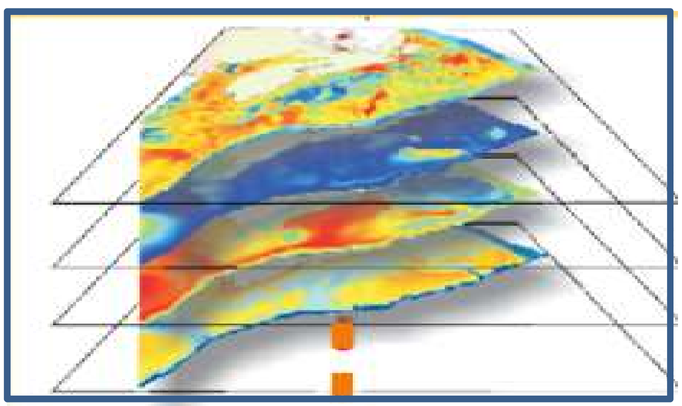
SPECIES

Biological Traits Species	Feeding mechanisms			Adult Longevity		
	SF	DF	GB	<2	2-5	>5
Mya arenaria	2	1	0	0	1	3
Mytilius galloprovincialis	3	0	0	0	1	3
Nereis rava	0	0	3	3	0	0
Terebellides stroemii	0	3	0	0	0	3
Lagis koreni	0	3	0	3	1	0
...						

L

ENVIRONMENT

STATIONS



Q

ENVIRONMENT

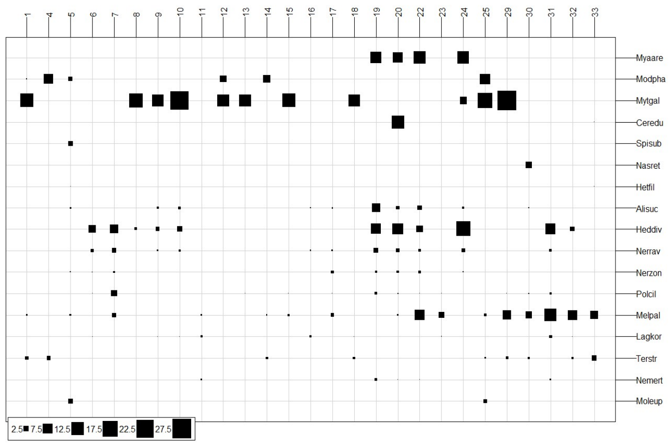
?

TRAITS

Species-Traits-Environment

STATIONS

SPECIES



R

TRAITS

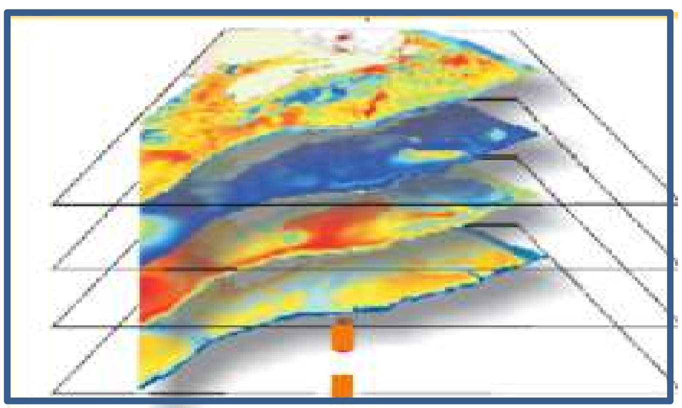
SPECIES

Biological Traits Species	Feeding mechanisms			Adult Longevity		
	SF	DF	GB	<2	2-5	>5
Mya arenaria	2	1	0	0	1	3
Mytilius galloprovincialis	3	0	0	0	1	3
Nereis rava	0	0	3	3	0	0
Terebellides stroemii	0	3	0	0	0	3
Lagis koreni	0	3	0	3	1	0
...						

L

ENVIRONMENT

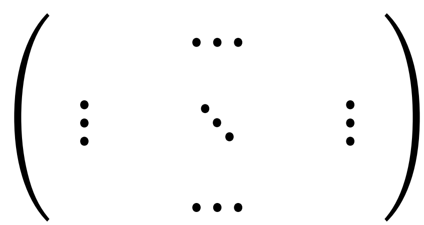
STATIONS



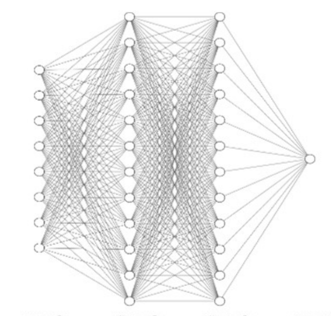
Q

TRAITS

ENVIRONMENT



+



RLQ

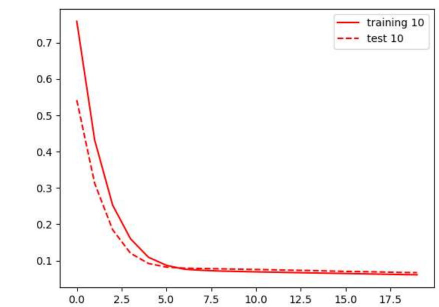
(Legendre **and Legendre, 2012 Dray et al., 2014)**

Neural Network

Neural Network modelling

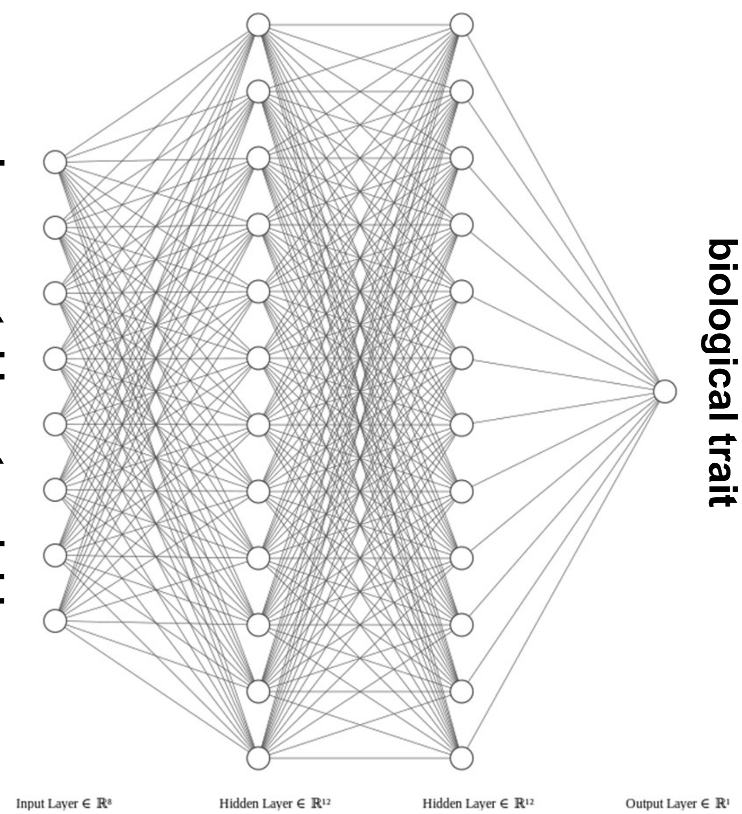
- 2 hidden layers with 12 neurons
- Training and testing data sets, 50 repetitions
- Selection of the most important variables: Input variables are removed one after the other and we keep variables that degrade the most the RMS when they are removed.
- Re-run the NN with the selected env. variables

Evolution of the RMS (training and test) during one repetition



- Substrate
- Température
- Salinity
- Total shear stress
- Oxygen
- POC flux to the bottom
- Carbon in the sediment
- PAR

environmental input variables



biological trait

Community weighted abundance of

- Method of sediments reworking
- Propensity to move through the sediment
- Feeding mechanisms
- Burrow Type
- Max sediment dwelling depth

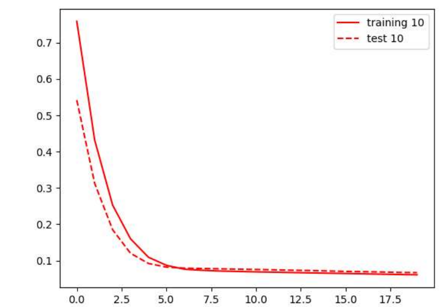
BPc

IPc

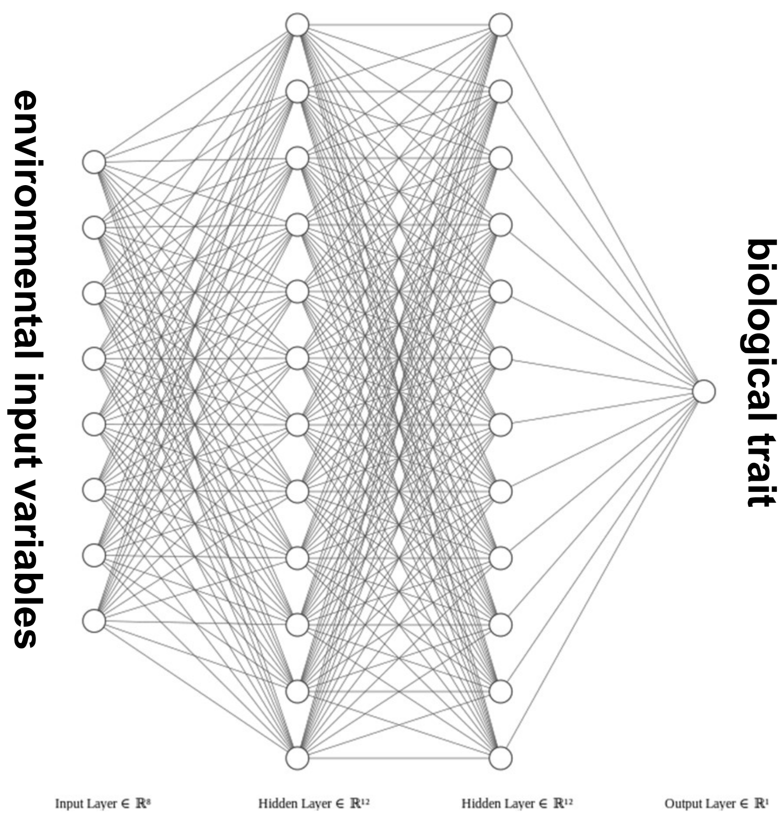
Neural Network modelling

- 2 hidden layers with 12 neurons
- Training and testing data sets, 50 repetitions
- Selection of the most important variables: Input variables are removed one after the other and we keep variables that degrade the most the RMS when they are removed.
- Re-run the NN with the selected env. variables

Evolution of the RMS (training and test) during one repetition



- Oxygen
- POC flux to the bottom
- Substrate
- Température
- Salinity



Community weighted abundance of

- Method of sediments reworking
- Propensity to move through the sediment
- Feeding mechanisms
- Burrow Type
- Max sediment dwelling depth

BPc

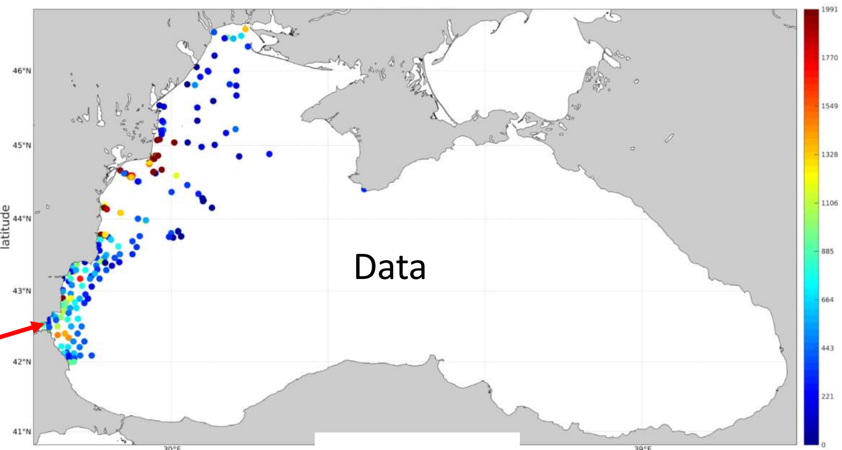
IPc

Neural Network modelling

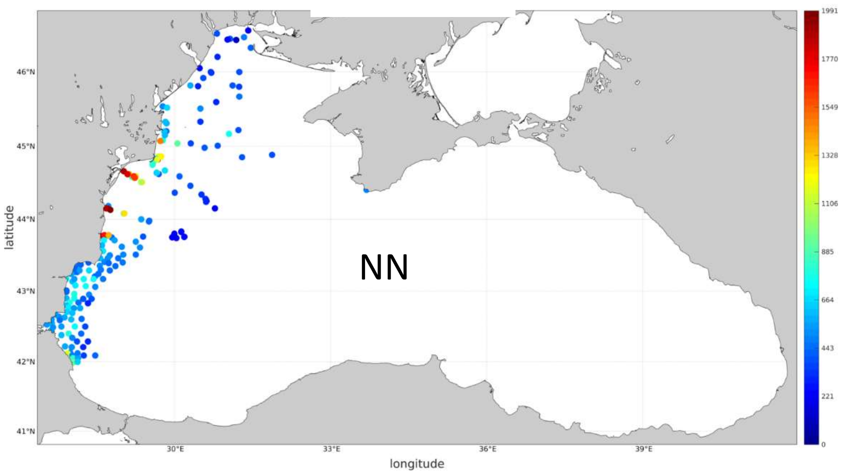
Bioturbation Potential

The NN fails to predict extreme/rare values (lack of training data)

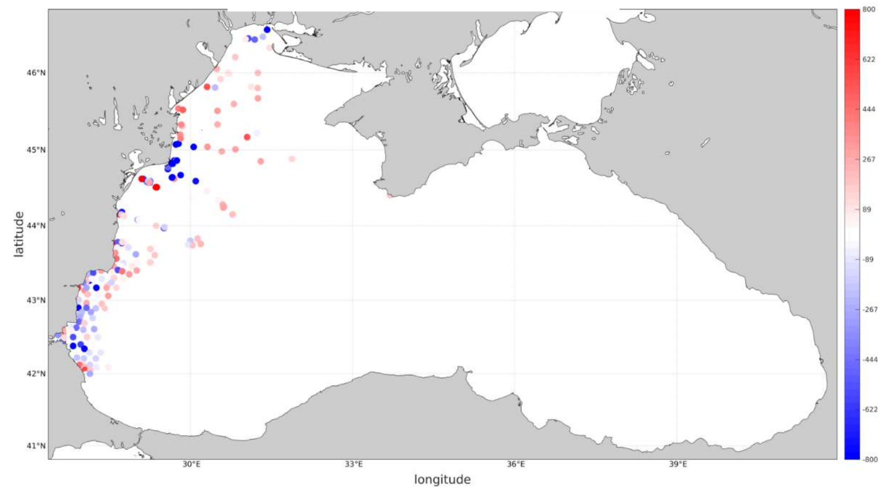
BPc Data

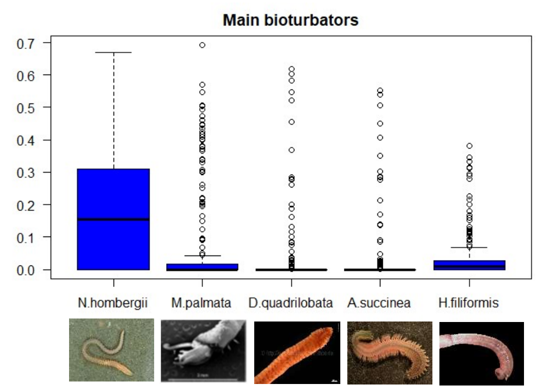


BPc Model



BPc Bias (Model-Data)





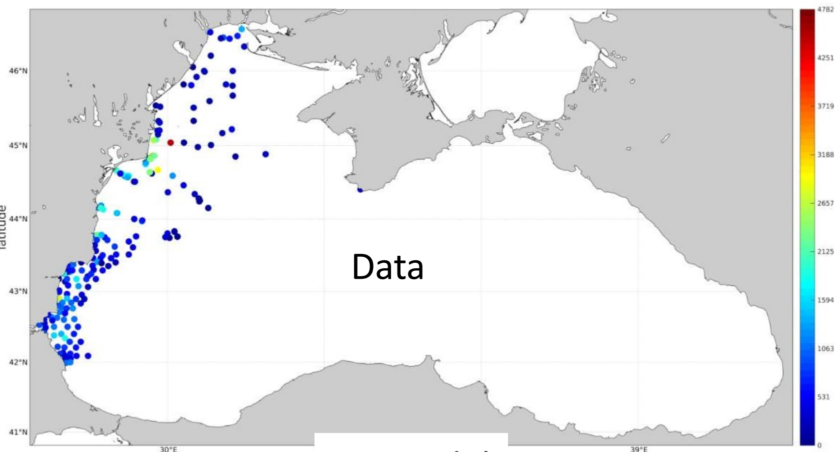
17% 15% 9% 8% 5%

Neural Network modelling

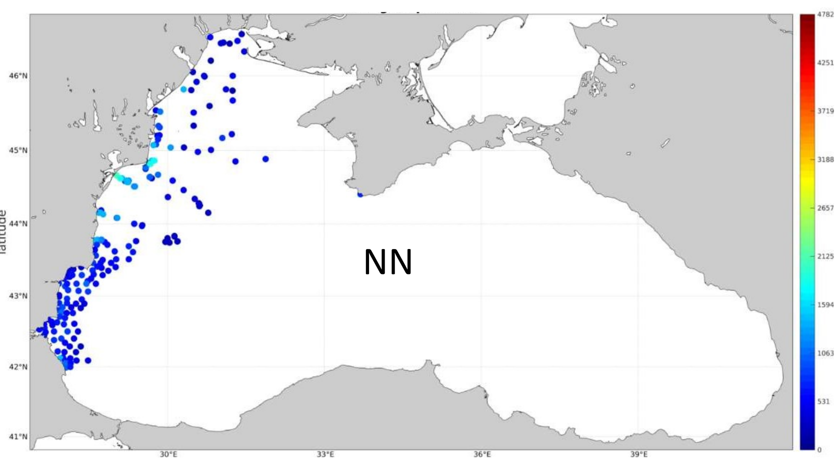
BioIrrigation Potential

The NN fails to predict extreme/rare values (lack of training data)

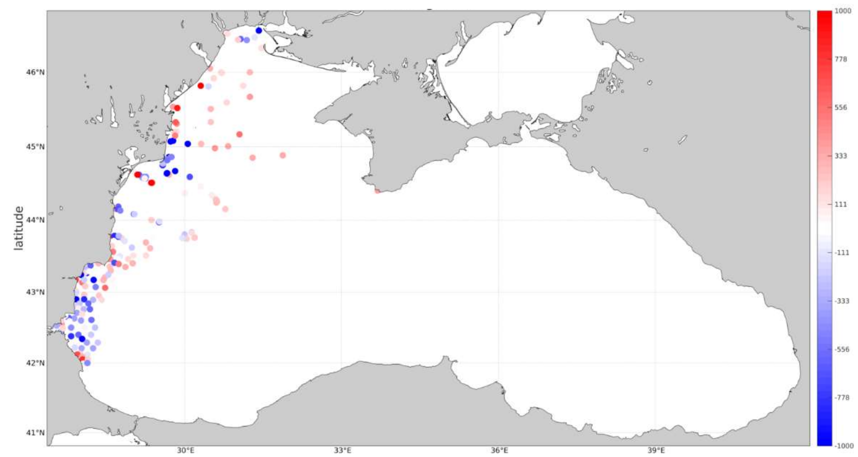
IPc Data

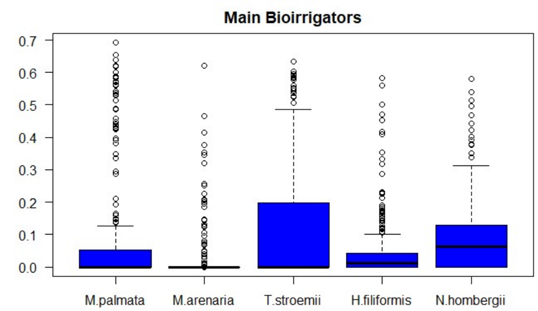


IPc Model



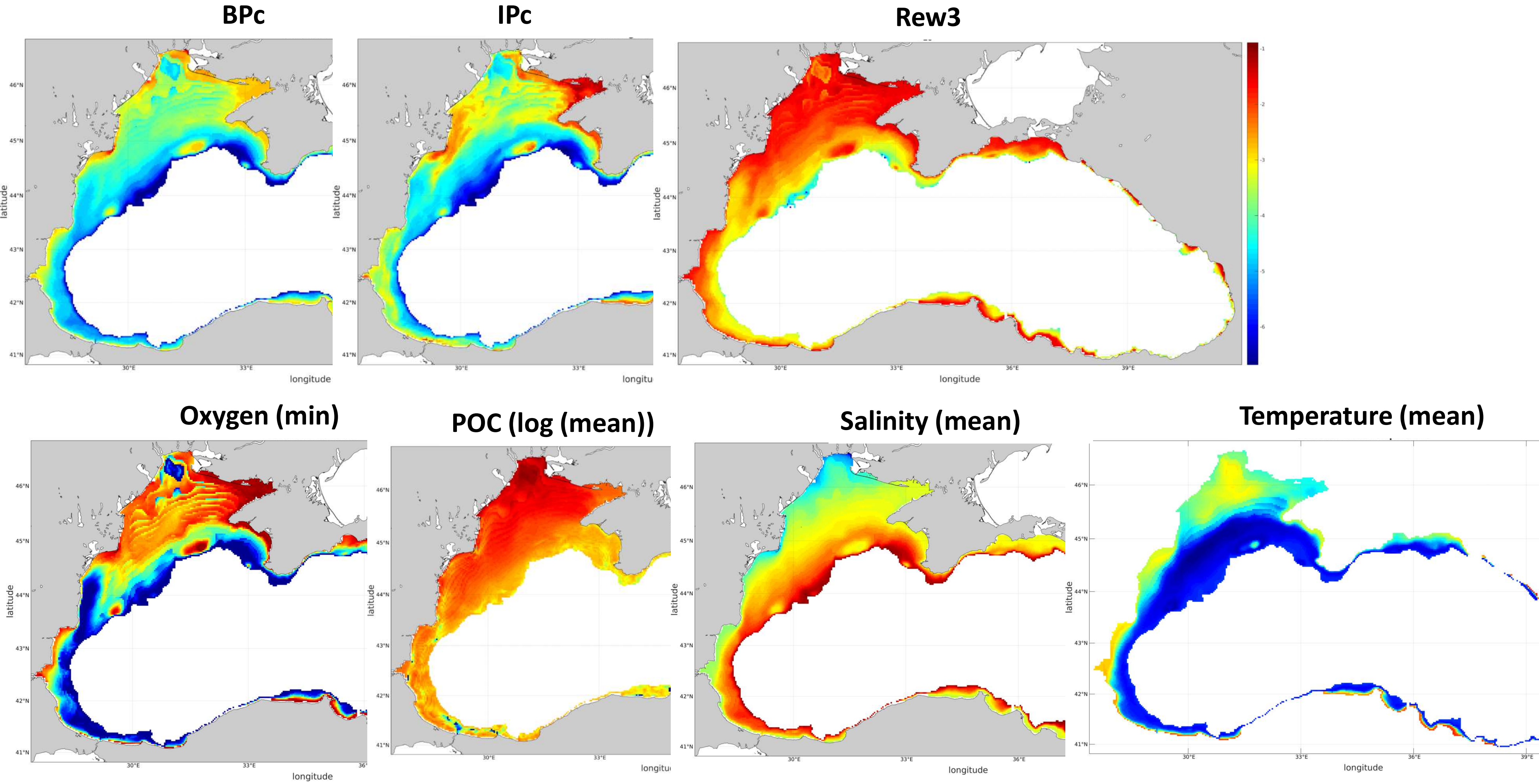
IPc Bias (Model-Data)





30% 10% 8% 6% 6%

Mapping (Fall 2017)



Take-home messages

- Bottom oxygen (mean and min), bottom carbon flux and also mud:sand ratio, bottom temperature and salinity are the environmental variables that selected by the NN for the mapping of the traits.

- NN has good performances (especially for normally distributed traits) but fails to predict extreme values that are rarely sampled. A dedicated data collection protocol targeting regions of high gradients, extreme and rare values is needed to better train the network.

- Traits distribution models are still lagging behind species distribution models. An extension of traits databases will facilitate their development.

- A combination of experimental work and machine learning tools will help to device new model parameterization.

From traits to model parameterization …

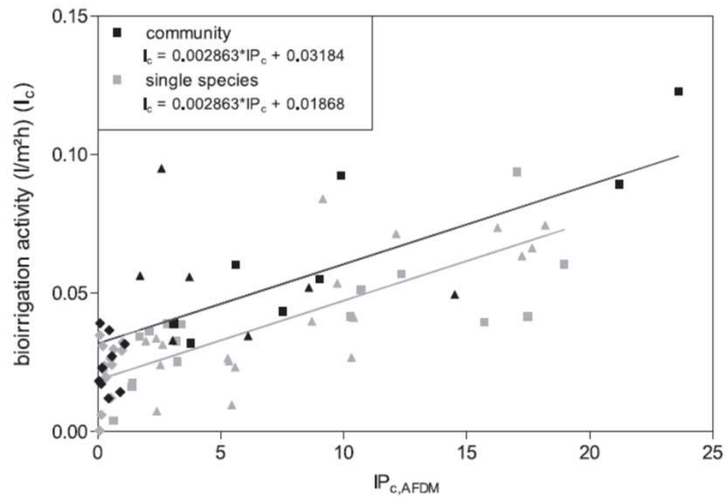
$\boldsymbol{Parameters\ (traits)}$

$\boldsymbol{l_m}$**(BPc)**

$$\log\left(\frac{\frac{l_m}{6}}{1-\frac{l_m}{6}}\right) = 4.55 + 0.719\log(BP_c)$$

Established for the Galway Bay by Solan et al., 2004

$\boldsymbol{BioIrrActivity}$**(IPc)**



Established from experiments Wrede et al., 2018

Thank you!