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The Trophic State of Shallow Lakes, remote sensors and ANN

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The trophic state of shallow lakes, remote sensors and ANN

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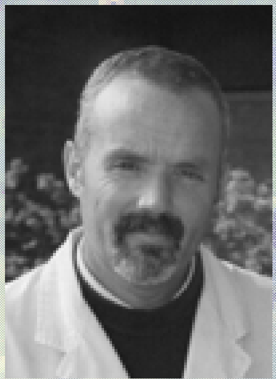
Universidad Nacional del Centro de la Provincia de Buenos Aires, Argentina

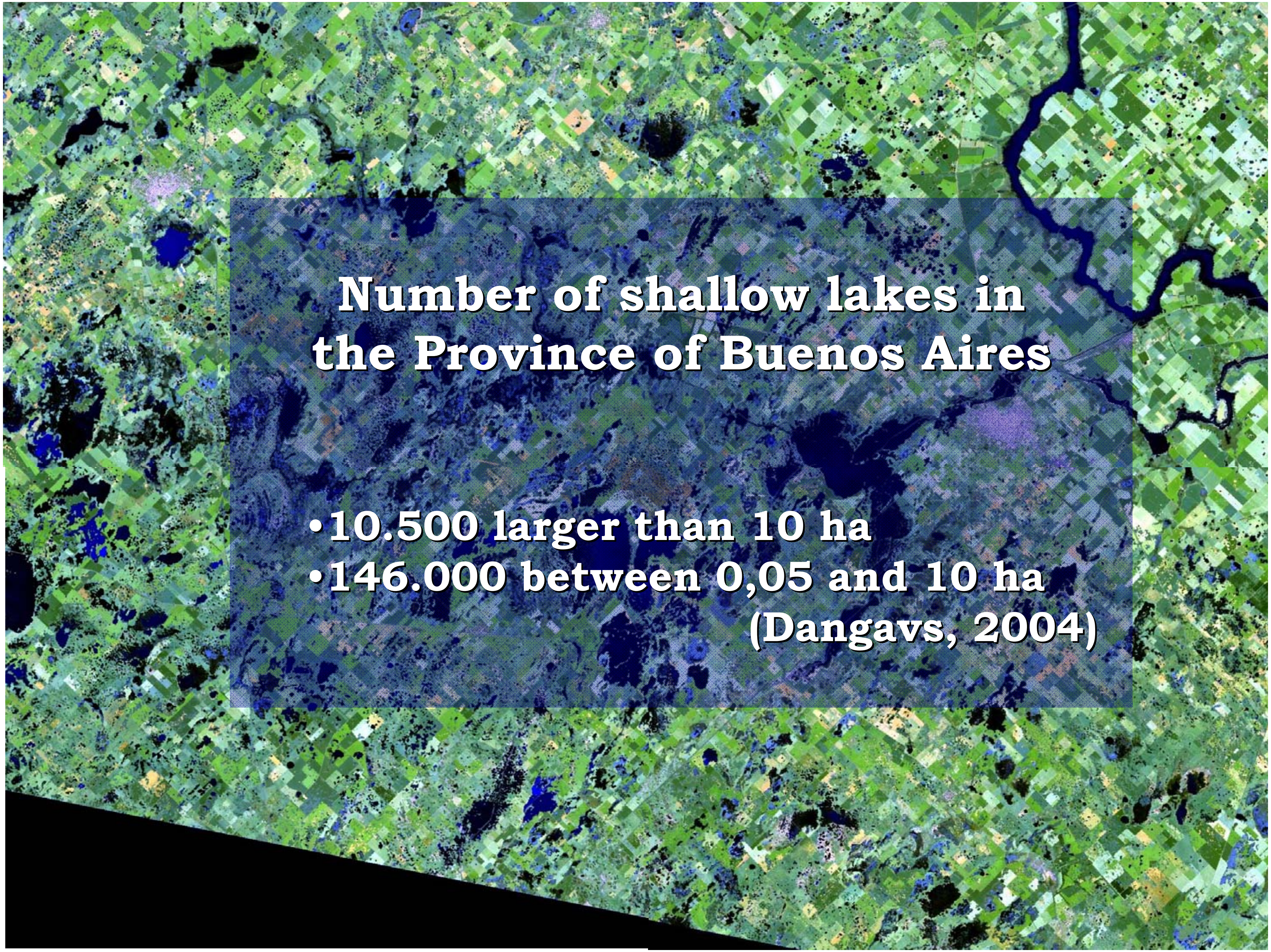
INSTITUTO MULTIDISCIPLINARIO SOBRE ECOSISTEMAS Y DESARROLLO SUSTENTABLE

Work Team

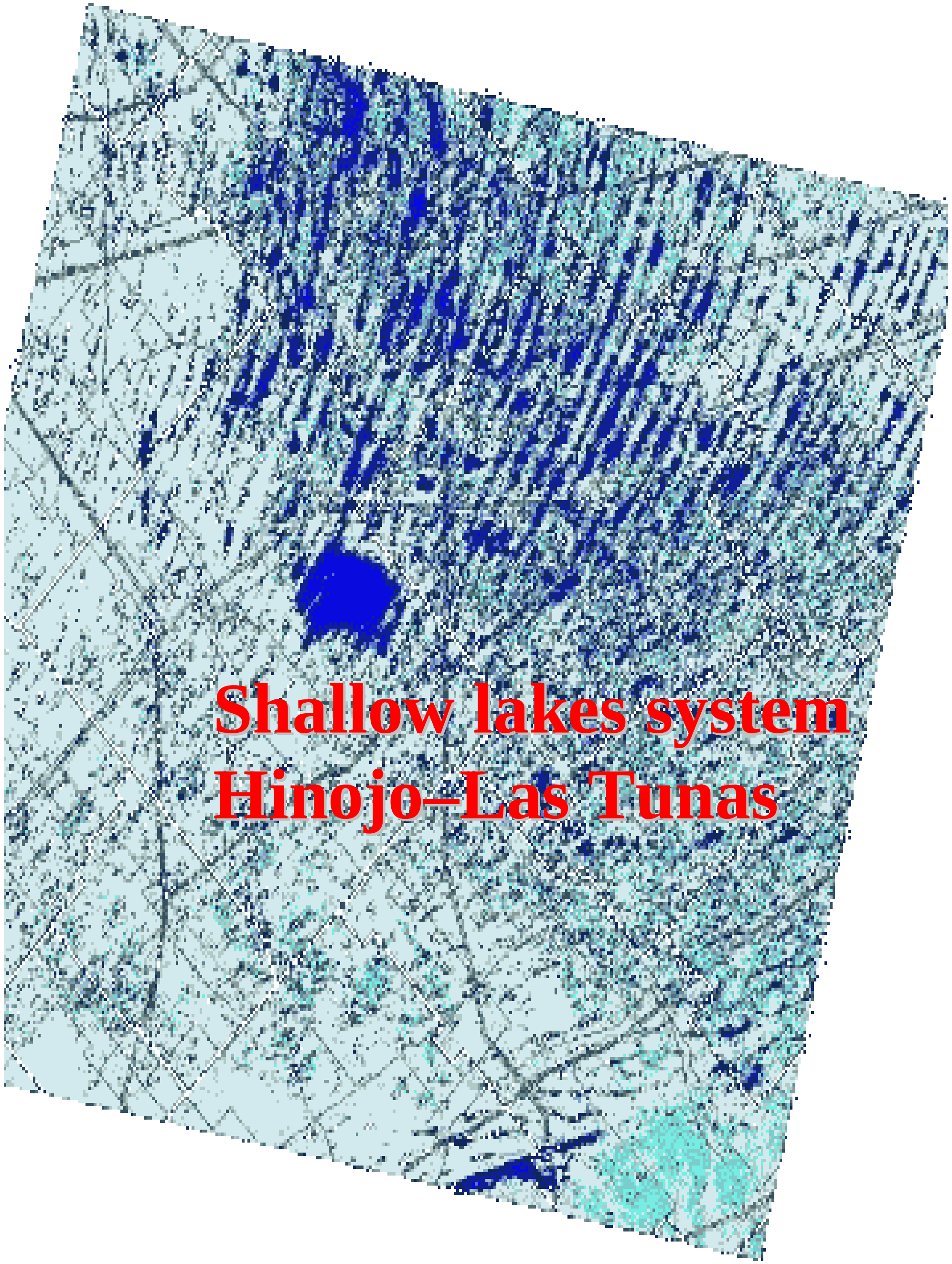


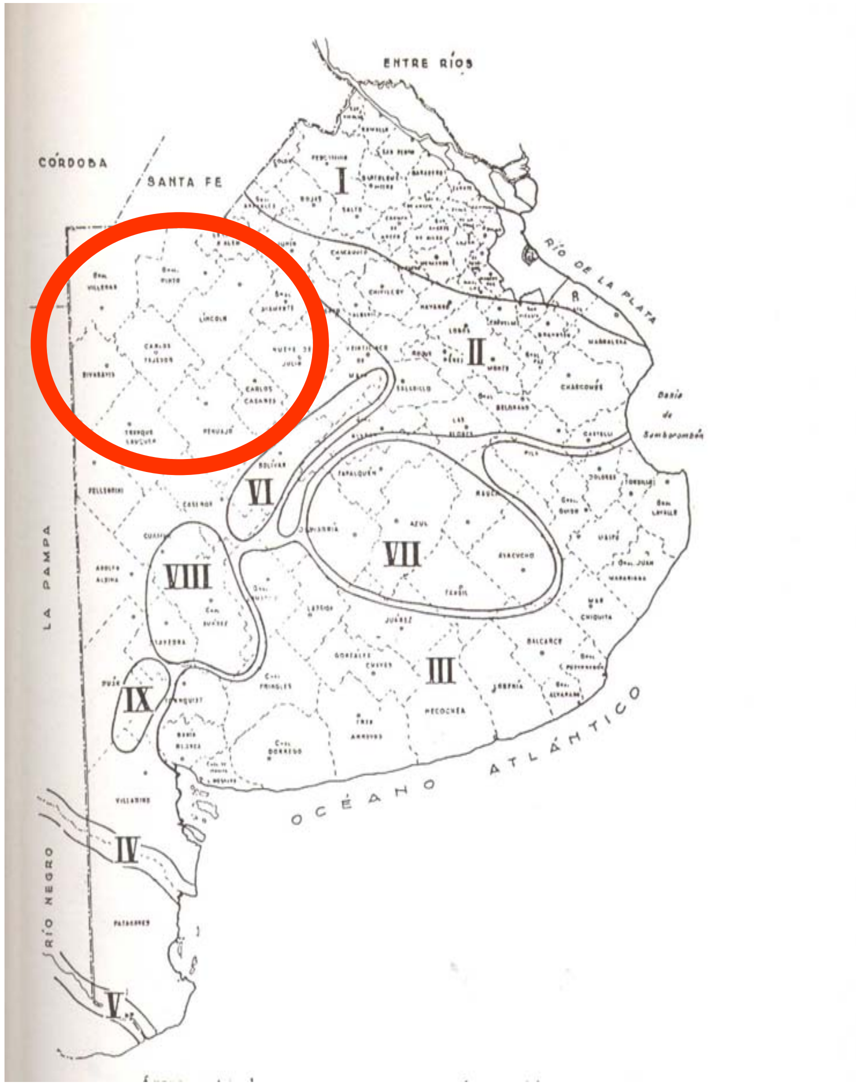




Number of shallow lakes in
the Province of Buenos Aires
•10.500 larger than 10 ha
•146.000 between 0,05 and 10 ha
(Dangavs, 2004)

Distribution in the Province





Bassins from Ringuelet, 1962

- Low depth determines instability, accelerated biogeochemical cycles, polymictic.
- Flat bottom, wide littoral
- No thermal or chemical stratification
- Low transparency
- Color: green, brown, clear
- Alternate equilibria: (clear waters = macrophytes; green = phytoplankton)
- Highly variable water permanence time and salinity (mostly oligo- to mesohalines)
- Naturally eutrophic, very productive
- Surrounded by reed
- Tend to marshes or dry to salt pockets.

- Hydrologically unstable:
  permanent, semipermanent,
  temporary, ephemerous

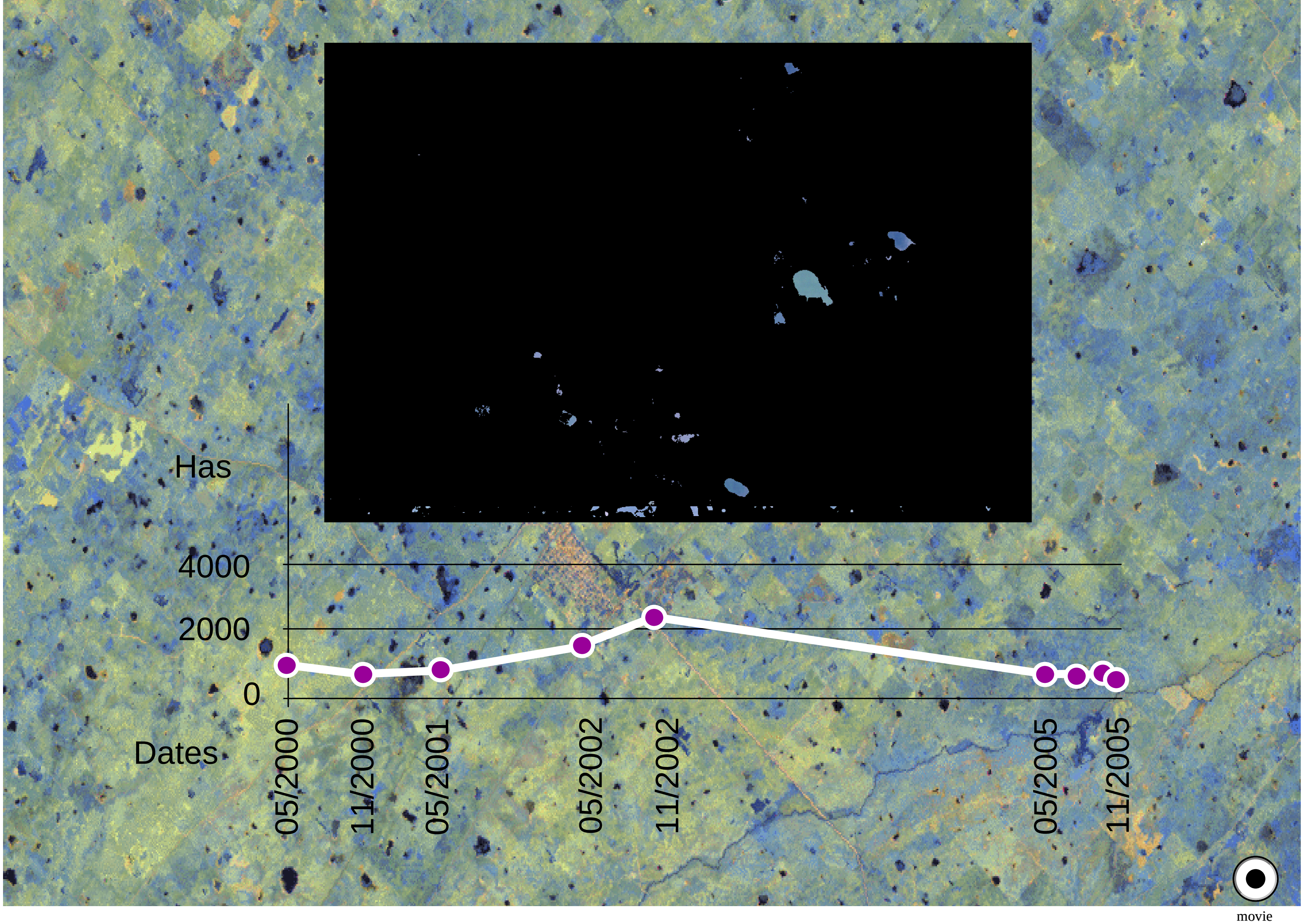
- Instability of water input: precipitations generate variation of volume and area

- Changing shape and size

- Both water and sediments are disturbed by winds.

- Measured chlorophyll values between 45 and 1400 mg/m3, dissolved matter values between 440 and 2300 mg/l, and 500 and 2880 mg/l for total solids.

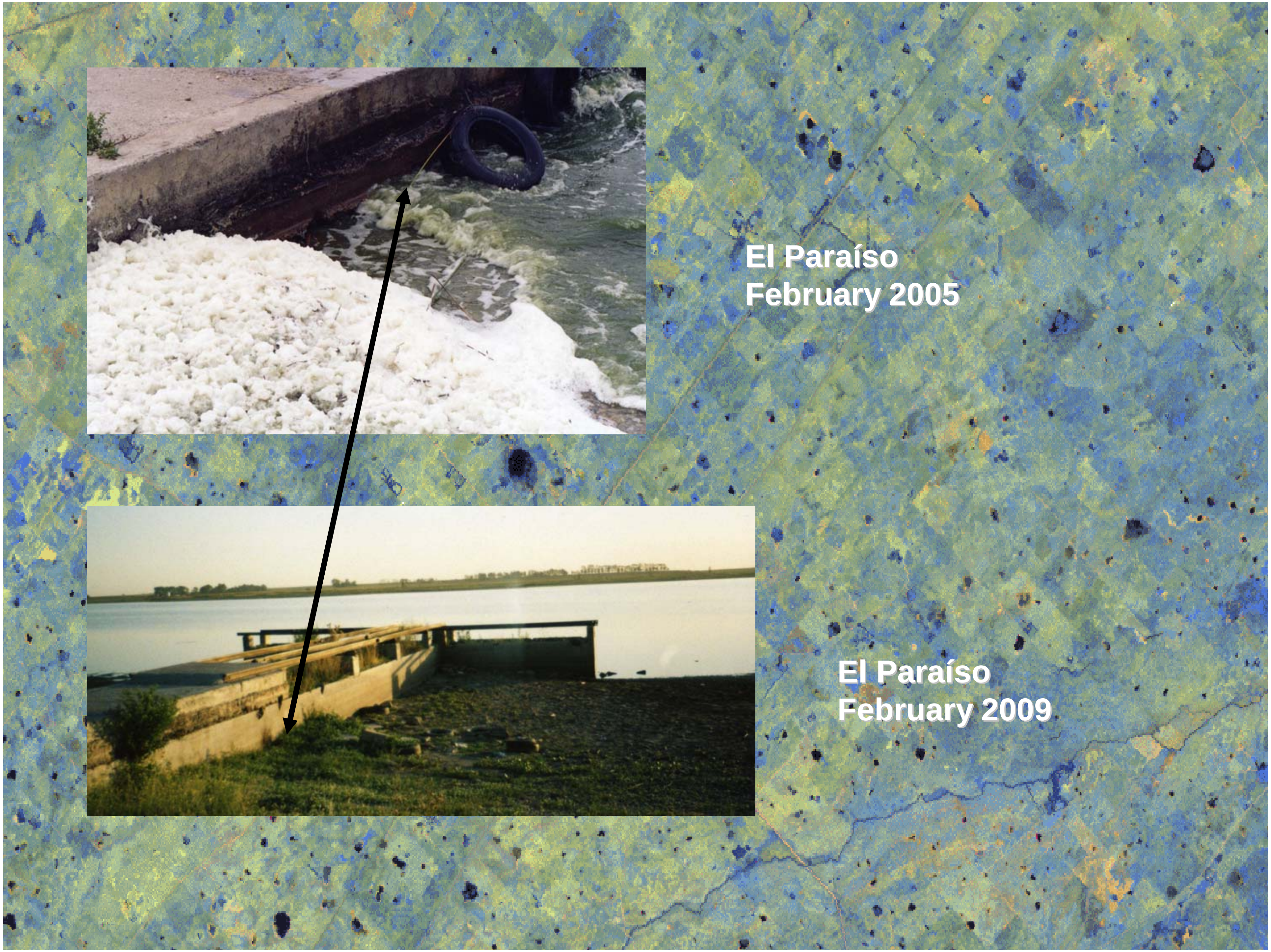
Variability



movie

Laguna Del Estado
January 2005

Laguna Del Estado
January 2006


El Paraíso
February 2005
El Paraíso
February 2009

Quilla Lauquen
January 2005

Quilla Lauquen
February 2009


La Peregrina
February 2005
La Peregrina
February 2009

La Brava
October 2005

La Brava
October 2009

Objectives

- Gain knowledge of the structure and functioning of the natural and socioeconomic components of the shallow lakes

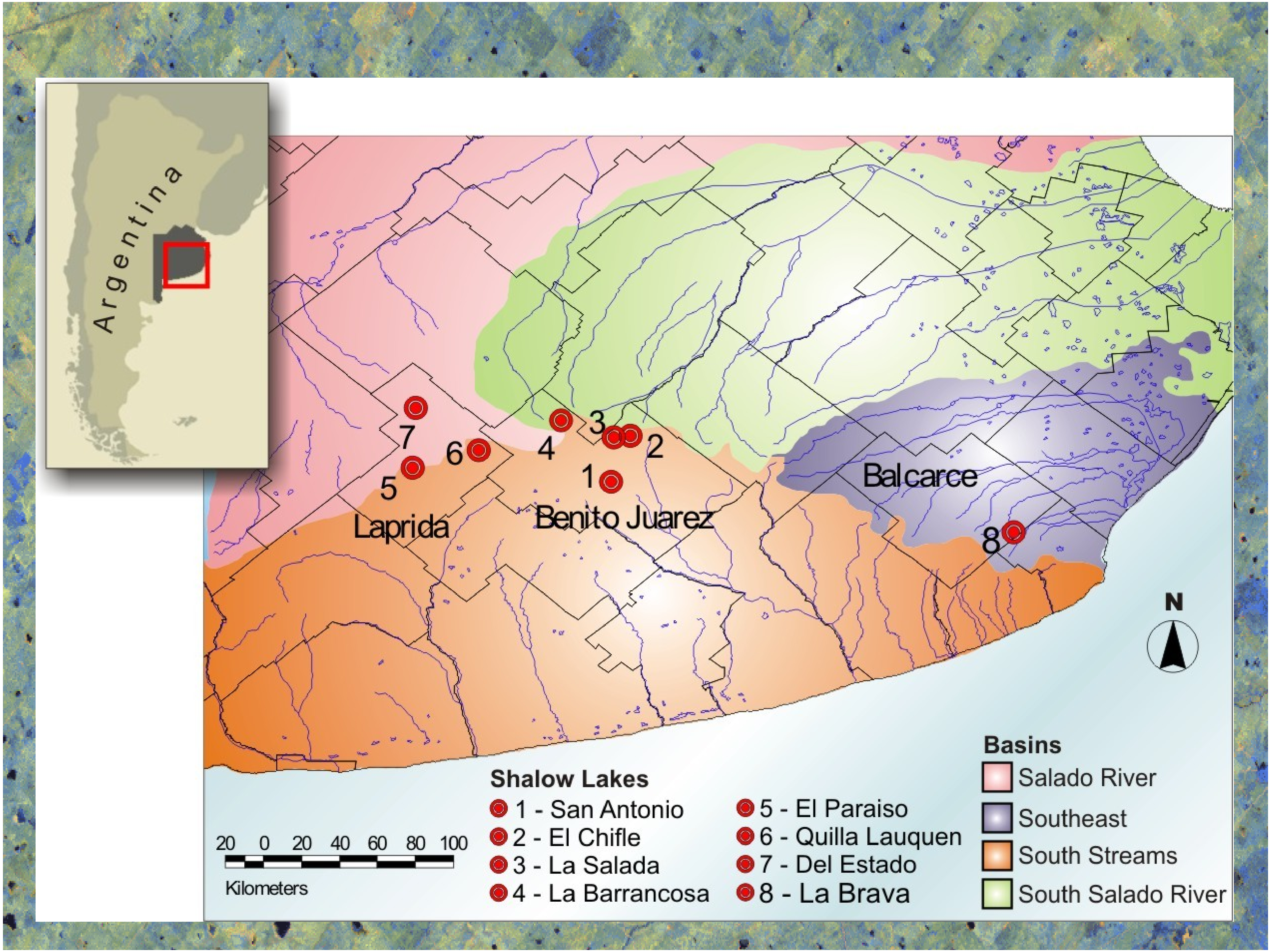
- Develop new observation and monitoring tools

- Integrate field data and remote sensors data

- Propose management strategies for shallow lakes taking into account socioeconomic, environmental and cultural aspects that have an impact on their dynamics.

Study sites

Different shallow lakes were selected based on their hydrological characteristics, location, accesibility, trophic structure, site use, and bassin land use.



Argentina
7
6
4
3
2
5
1
Laprida
Benito Juarez
Balcarce
8
N
Shalow Lakes
1 - San Antonio
2 - El Chifle
3 - La Salada
4 - La Barrancosa
5 - El Paraiso
6 - Quilla Lauquen
7 - Del Estado
8 - La Brava
Basins
Salado River
Southeast
South Streams
South Salado River
20 0 20 40 60 80 100
Kilometers

PHYSICO-CHEMICAL PARAMETERS (O, TEMP, SECCHI DEPTH, PH, CONDUCTIVITY, DOM, etc.)

NUTRIENTS (TP, SEDIMENTS)

PLANKTON (PHYTO and ZOO)

MACROPHYTES (IDENTIFICATON, DISTRIBUTION)

FISH (Emphasis in this community)

IN PARTICULAR CASES heavy metals, pesticides in water, sediments and organisms


FISH

- DIVERSITY
- % OF CAPTURES (IN NUMBERS AND WEIGHT)
- CPUE OF “PEJERREY” (*Odontesthes bonariensis*)
- CONDITION (FACTOR K, IC, LENGTH – WEIGHT,
  RELATIVE WEIGHT)
- GROWTH (SCALES)
- SIZE DISTRIBUTION IN CAPTURES
- GUT CONTENTS
- AVERAGE LENGTH AND WEIGHT
- GONADS (% SEXES, IGS, STAGES)

Classification

Shallow Lake	Secchi Disk Depth [cm] min – max (mean)	Chlorophyll *a* [mg/m^3] min - max (mean-median)	Total Solids [mg/l] min - max (mean-median)
La Brava	37 – 37 (37)	45.3 - 45.3 (45.3-45.3)	507 – 507 (507-507)
Quilla Lauquen	10 – 22 (16)	76.3 - 122.1 (99.2-99.2)	806 – 812 (809.0-809)
San Antonio	18 – 36 (26.2)	50.4 - 179.8 (101.4-94.0)	1296 – 1418 (1376.6-1396)
La Barrancosa	11.5 – 27 (19.5)	71.3 - 155.4 (110.5-95.7)	1327 – 1659 (1559.1-1624)
La Salada	13 – 23 (17.3)	112.0 - 260.2 (159.2-132.2)	1184 – 1284 (1241.3-1248.5)
El Chifle	7 – 23 (15.8)	120.9 - 249.9 (200.6-215.8)	1736 – 1953 (1846.8-1849)
El Paraiso	11 – 17 (14)	303.5 - 384.5 (353.9-369.0)	1498 – 1830 (1684.0-1700)
Del Estado	9 – 15.5 (9.5)	325.0 - 671.2 (559.5-600.8)	1788 – 2881 (2438.1-2522)

The values of chlorophyll-a and total solids (TS) in the samples and the Secchi disk depth were used to perform a classification of the shallow lakes from field data following their turbidity. An initial classification was done by defining the quantile probability distribution.

Classification

Four categories were later defined from the quantile probability distribution and the expertise acquired in the field:

•Class 1, formed by clear water shallow lakes

•Class 2, formed by shallow lakes presenting intermediate turbidity values

•Class 3, formed by shallow lakes exhibiting high values of chlorophyll

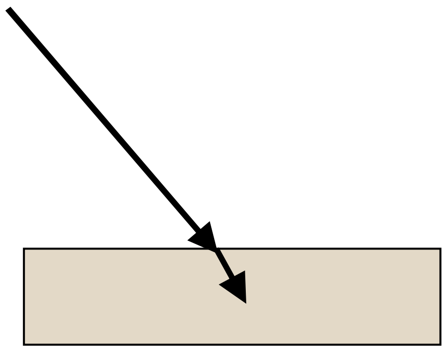
•Class 4, formed by shallow lakes exhibiting the highest values of chlorophyll and total solids.

Classification

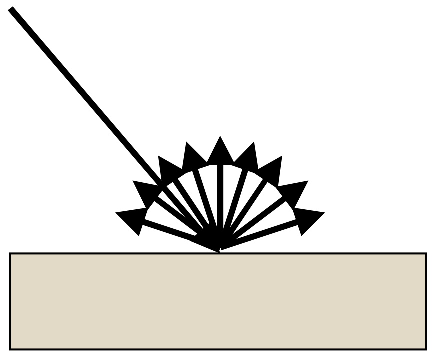
Class	Variable	Mean	Min	Max	Median	Q1	Q3
1	Chl *a*	60.80	45.30	76.30	60.80	45.30	76.30
	TS	659.50	507.00	812.00	659.50	507.00	812.00
	SDD	25.50	14.00	37.00	25.50	14.00	37.00
2	Chl *a*	130.03	50.40	260.20	117.50	93.20	155.40
	TS	1435.63	806.00	1953.00	1397.00	1284.00	1629.00
	SDD	20.63	11.50	36.00	19.00	17.00	23.00
3	Chl *a*	305.73	120.90	384.50	340.40	249.90	371.90
	TS	1728.29	1498.00	1942.00	1706.00	1686.00	1830.00
	SDD	13.71	10.00	17.00	15.00	11.00	16.00
4	Chl *a*	559.46	325.00	671.20	600.80	533.30	667.00
	TS	2438.20	1788.00	2881.00	2522.00	2347.00	2653.00
	SDD	9.00	7.00	10.00	9.00	9.00	10.00

Mean, minimum, maximum, median, first and third quantil values for chlorophyll-a, total solids (TS) and Secchi disk depth (SDD) defined for each class.

Introduction – Behavior of Light under Water



Absorption



Dispersion

Optic properties of water depend on suspended particles and on dissolved substances.

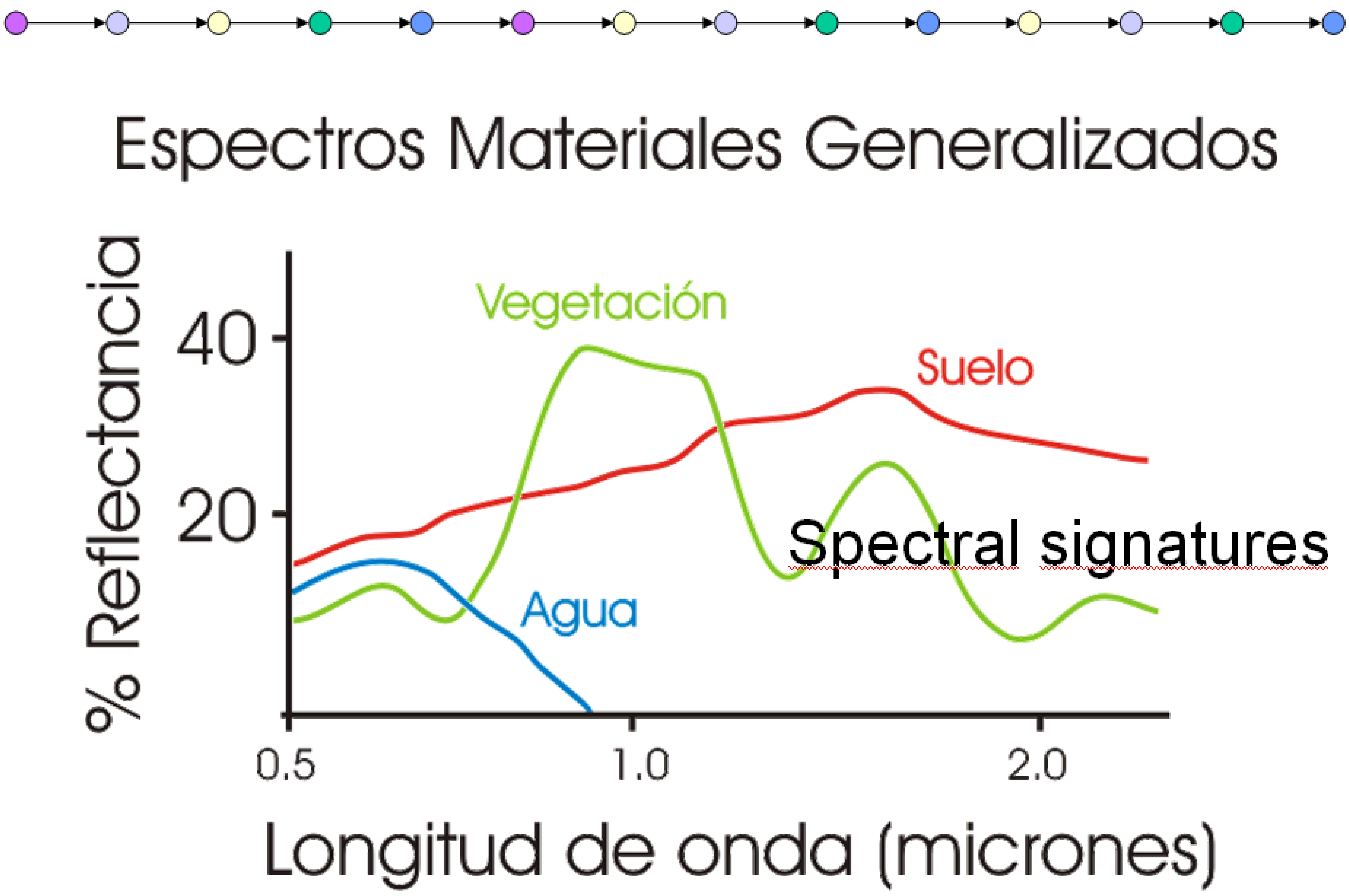
Introducción – Comportamiento de la Luz bajo el Agua

Absortion ⇨ **Suspended clay paricles**

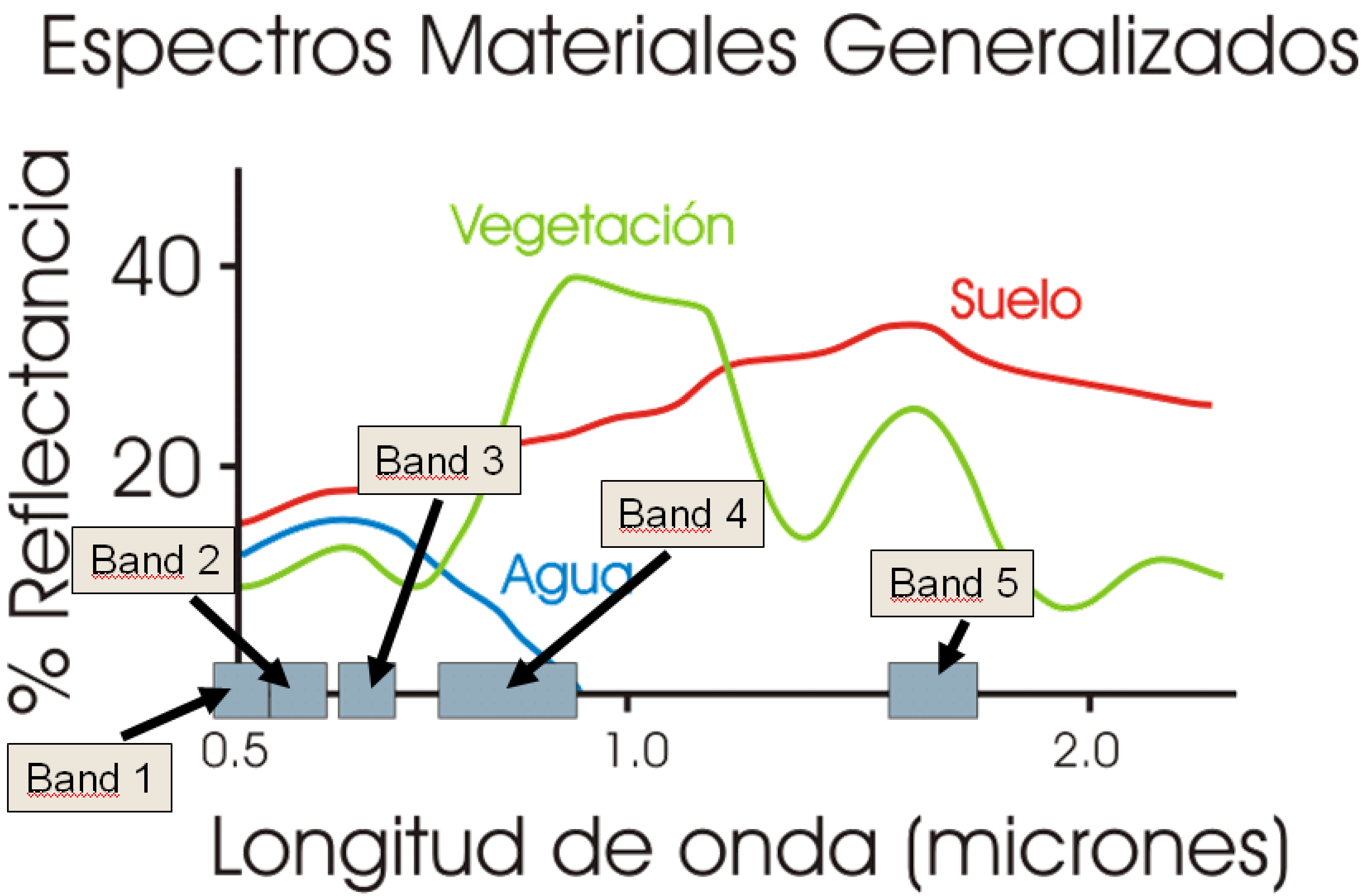
Dispersion ⇨ **Dissolved organic substances**

Absortion + Dispersion ⇨ **Phytoplankton**

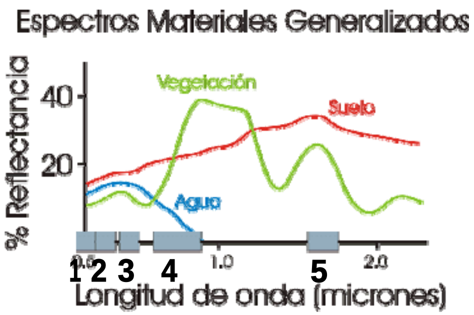
Introduction – Spectral signatures



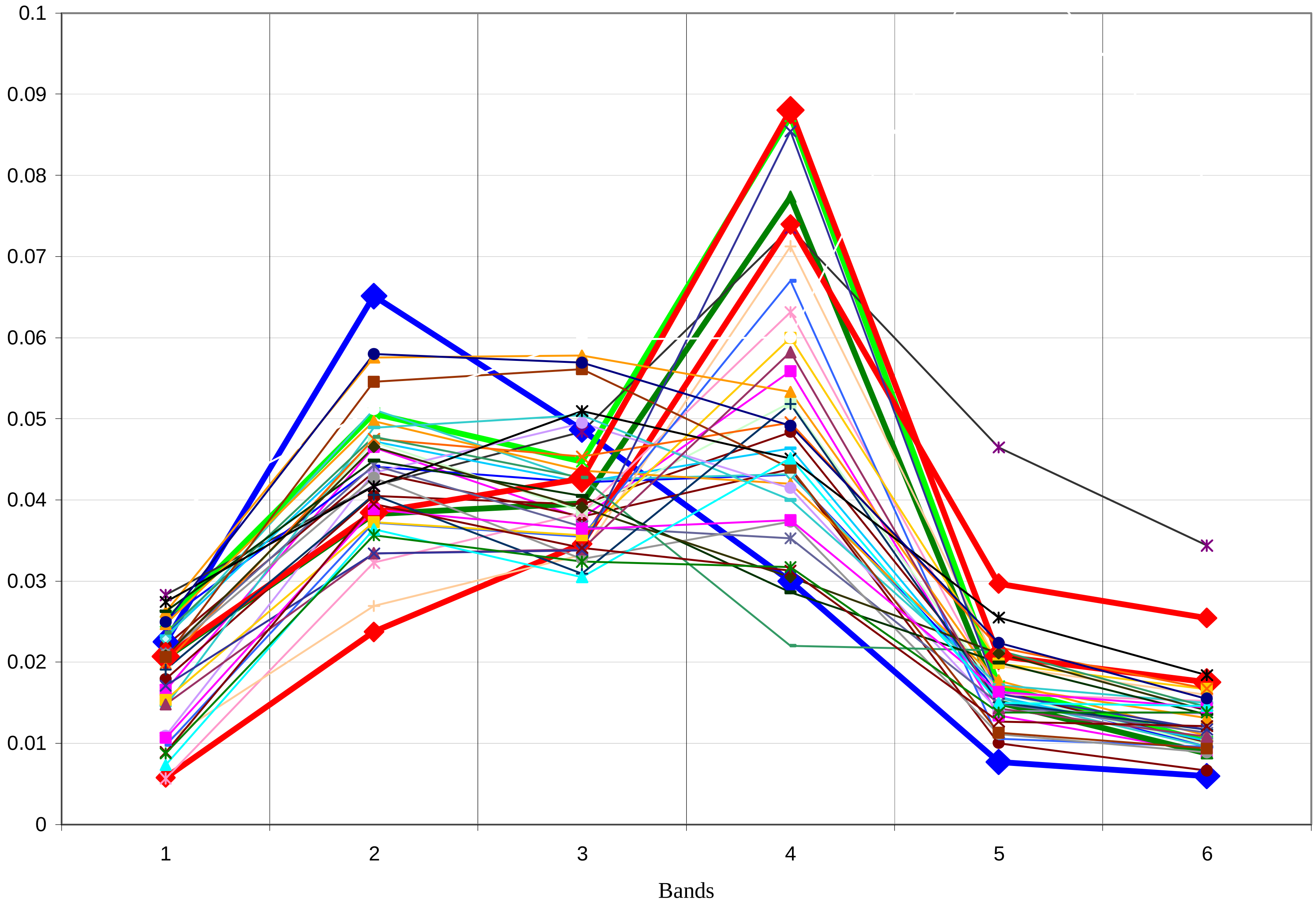
Introduction – Spectral signatures



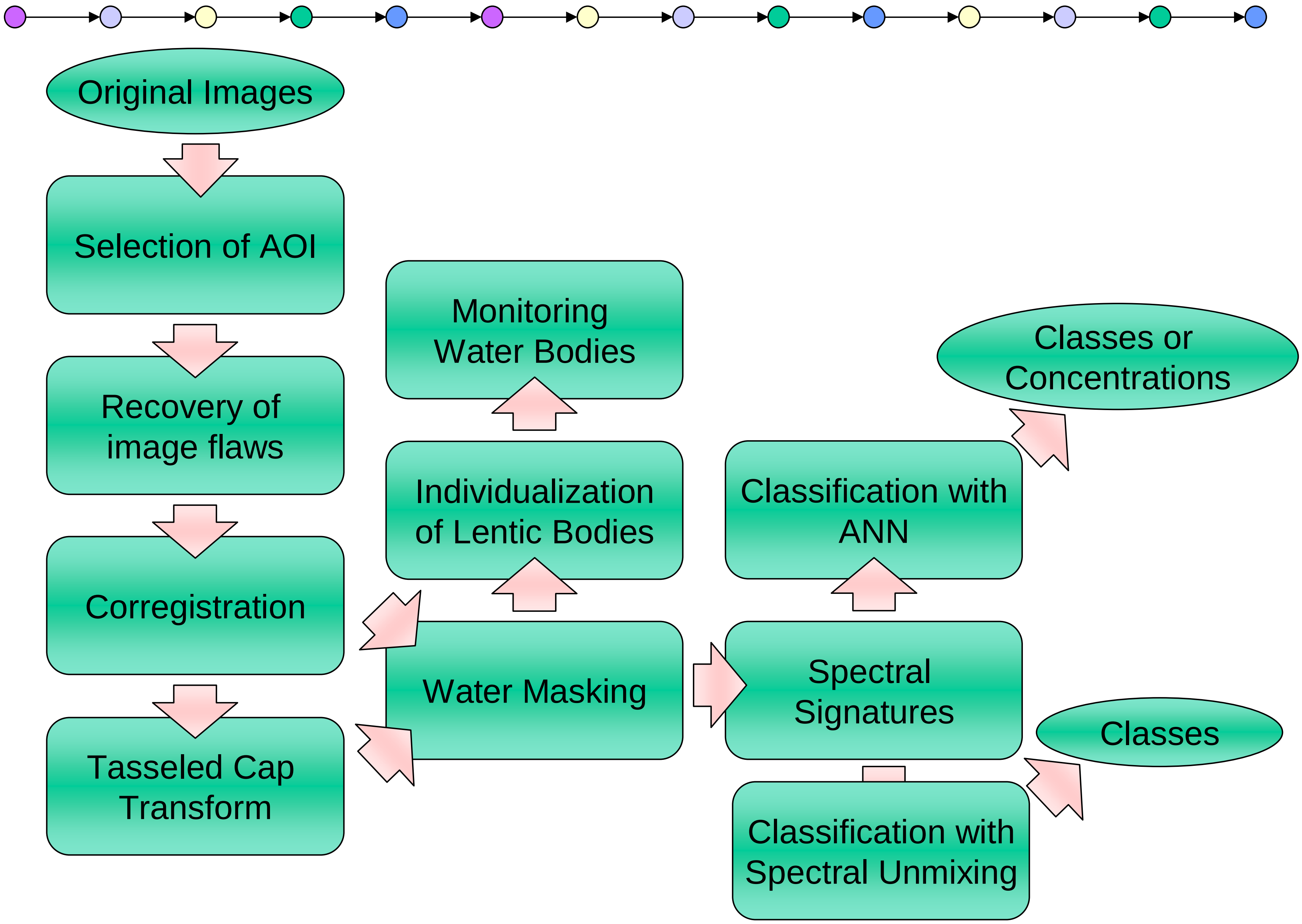
Introduction – Spectral signatures



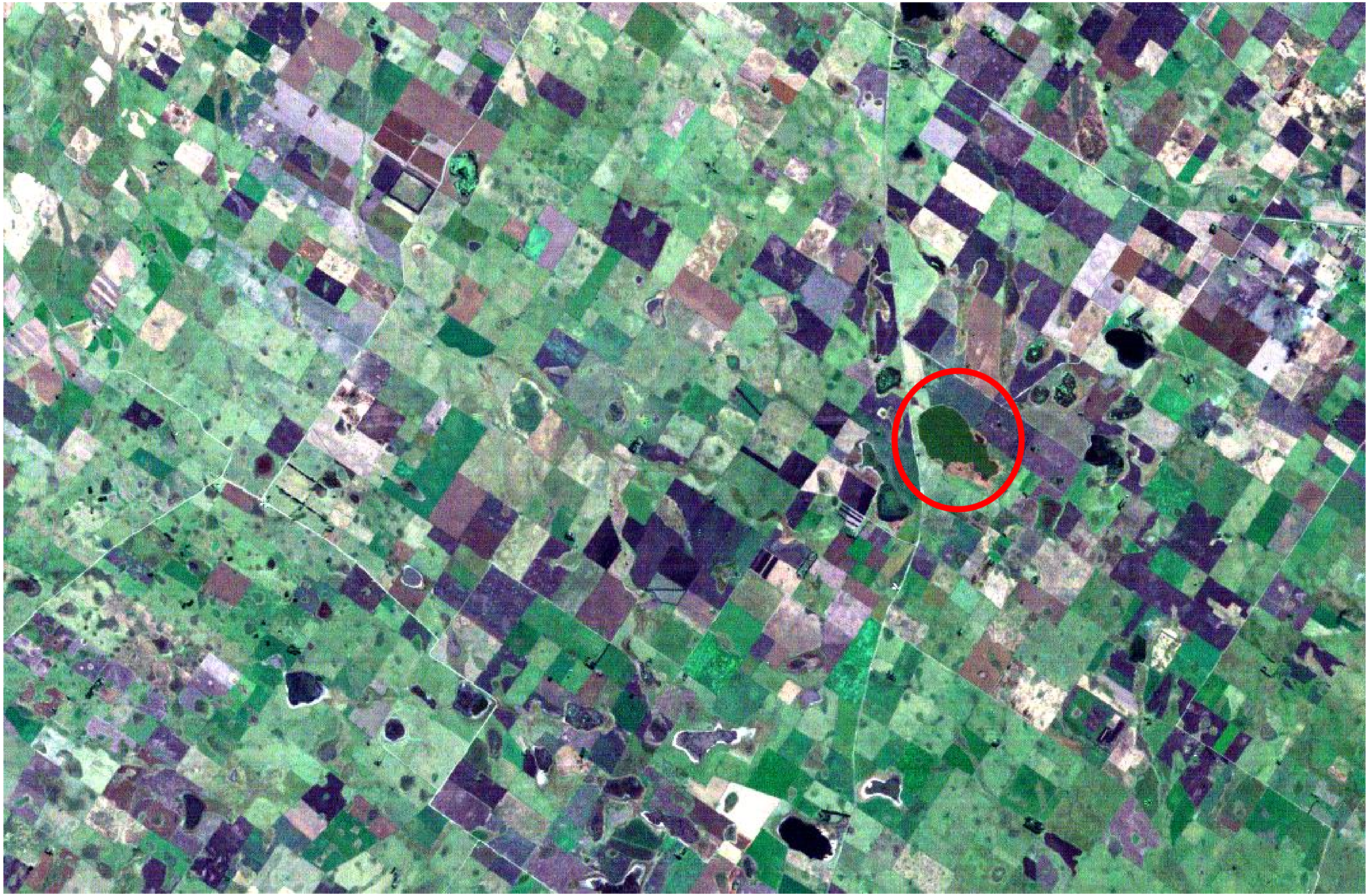
Introduction – Spectral signatures



Methodology

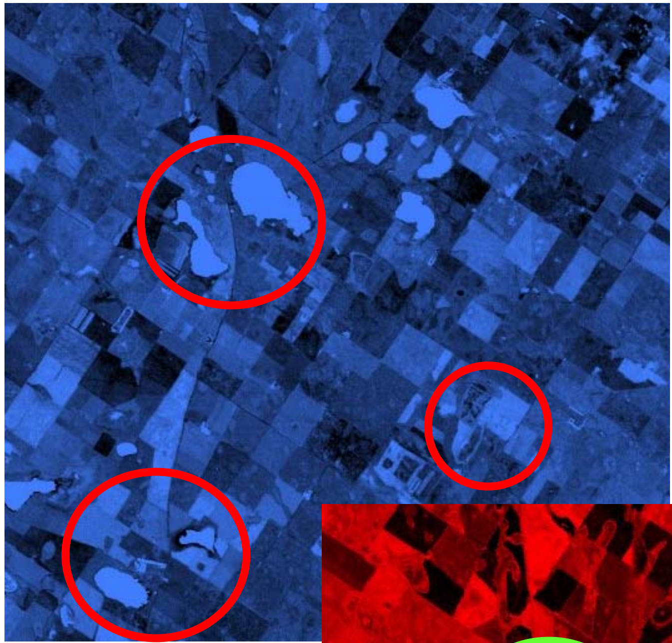


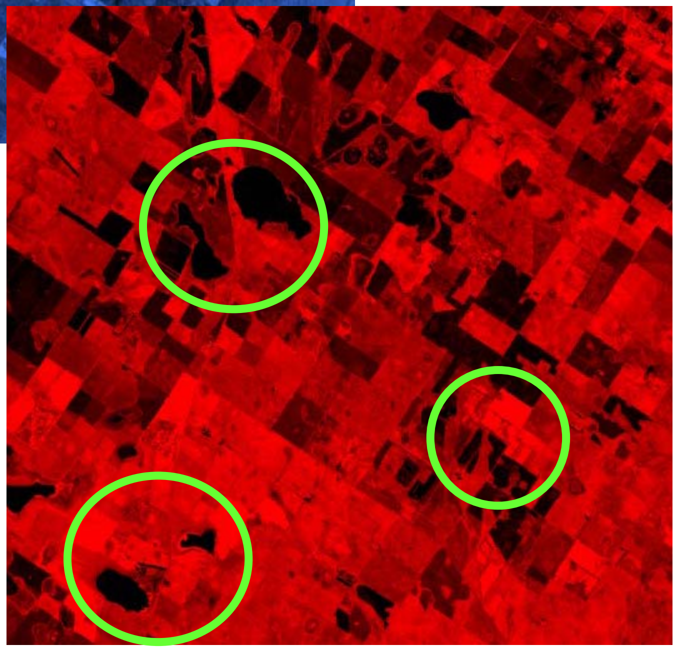
Selection of AOI



Water Mask

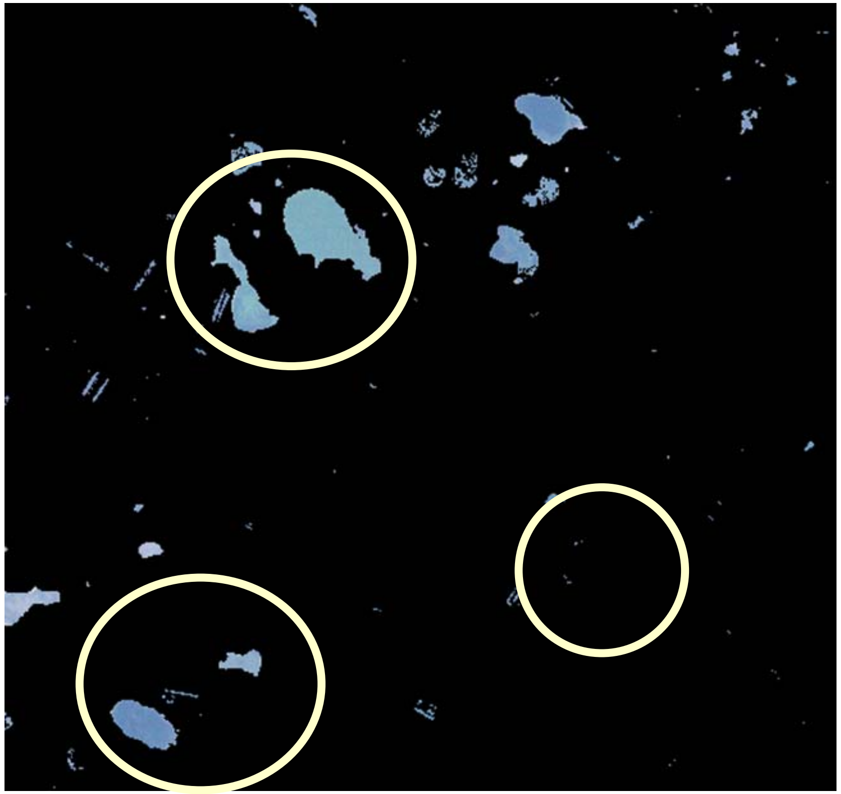
Wetness - Tasseled Cap



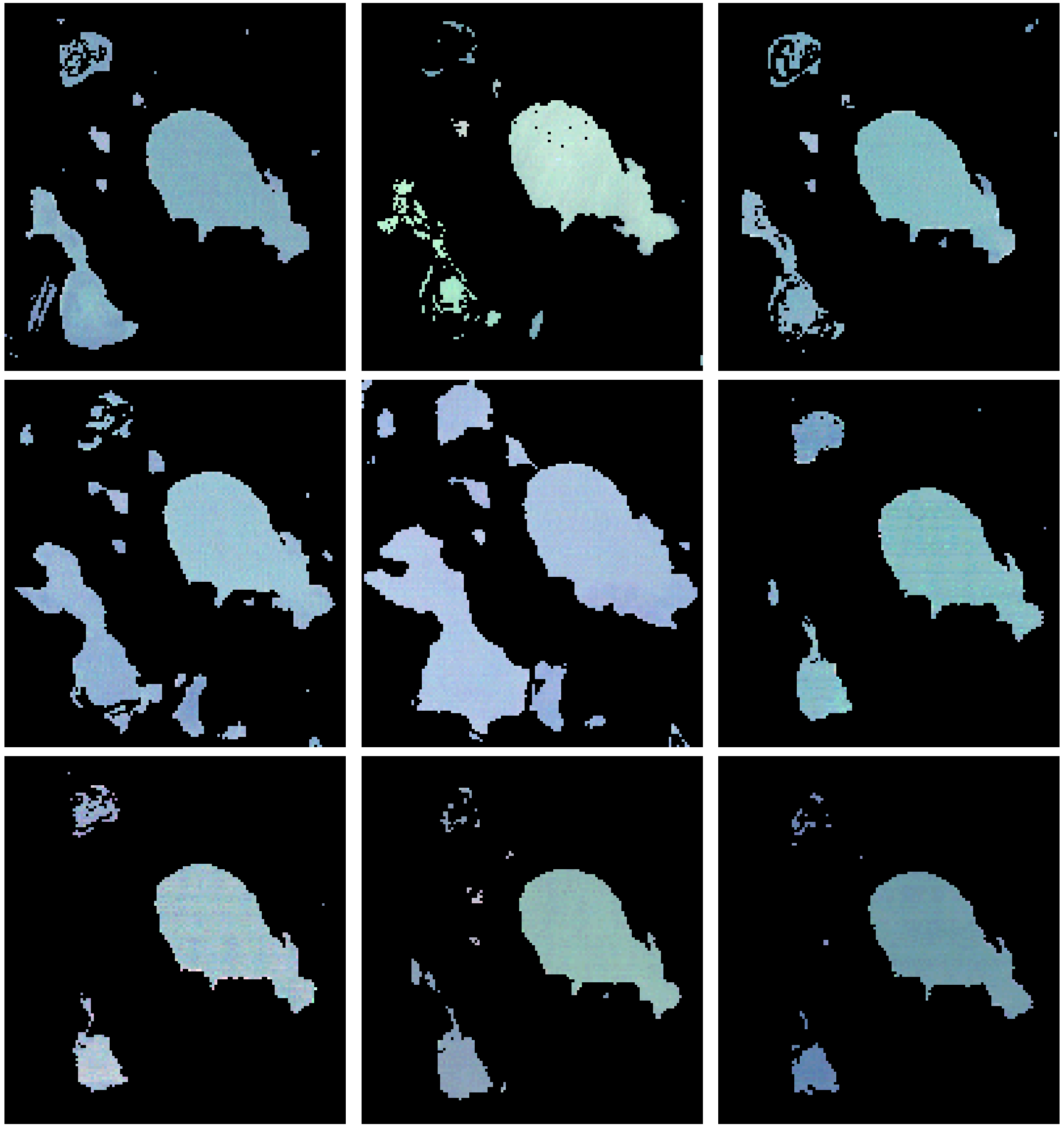


Brightness - Tasseled Cap

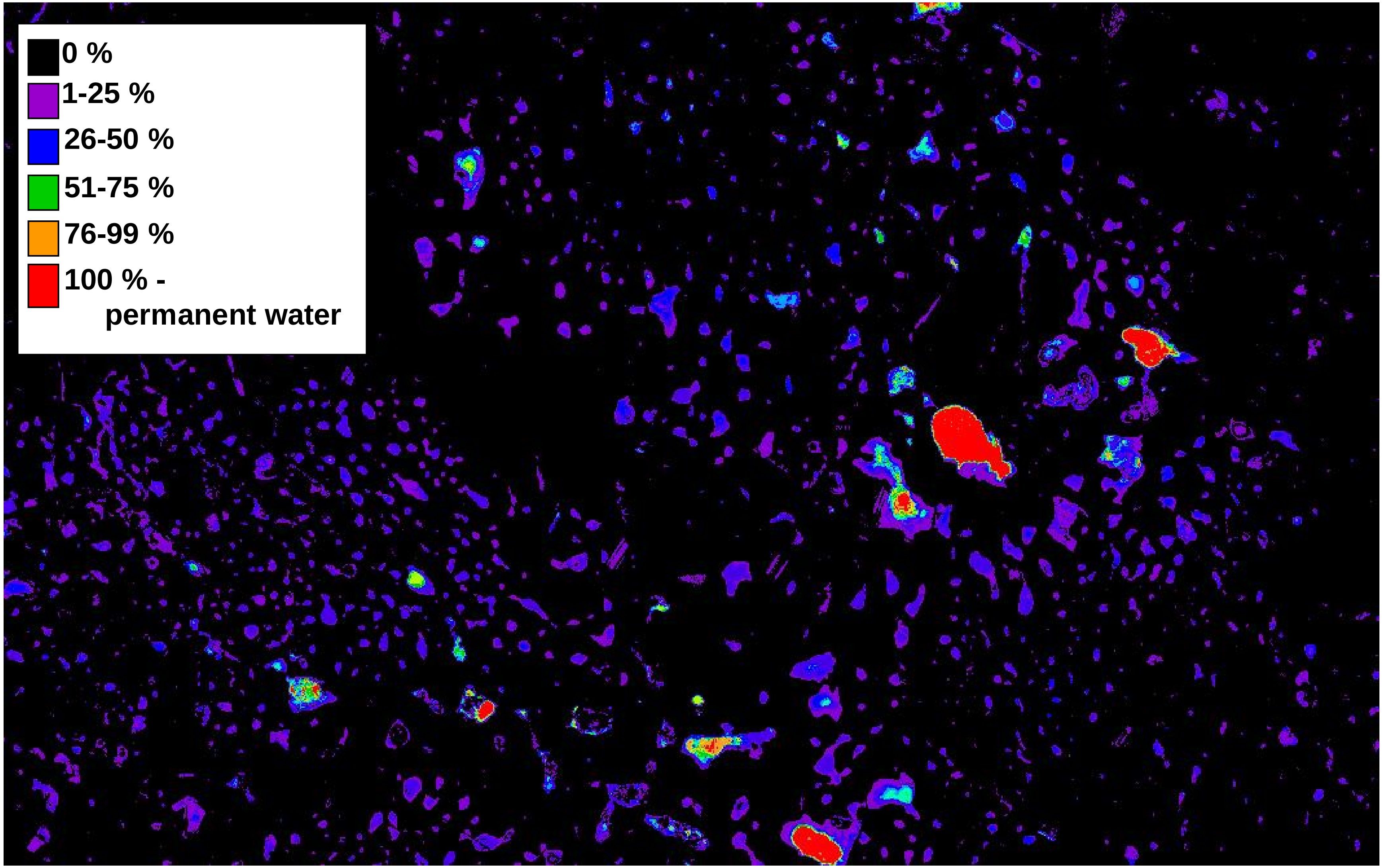
Water Bodies

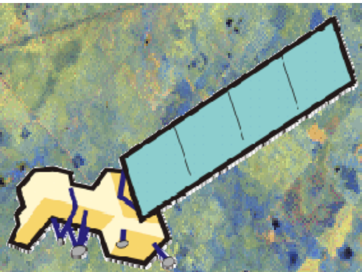


Water Masks



Recurrence Maps





Classification by Spectral Unmixing

The objective of the *spectral unmixing* method is to perform an analysis at the subpixel scale, focusing on determining the percentage of each constituent of the ground cover.

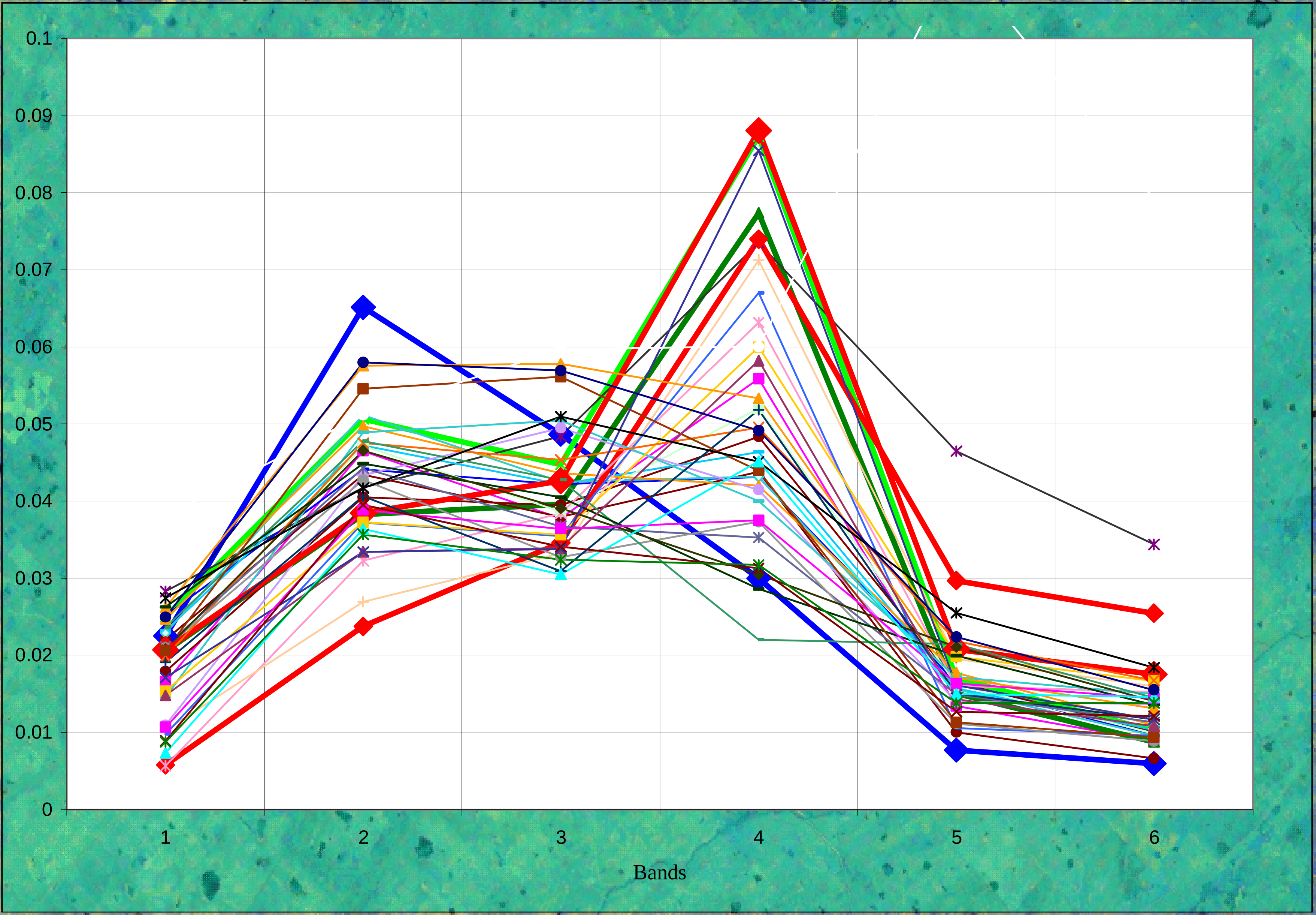
Each spectrum in a spectral dataset can be modeled as a linear combination of a finite number of spectrally distinct signatures (end-members), with coefficients or fractional abundances between 0 and 1 and adding up to one.

Classification by Spectral Unmixing

Each pixel in the image is a point or vector in an *n*-dimensional space, *n* depending on the number of available bands.

Each constituent of ground cover materials can thus be defined as an end-member (its spectral signature), and it is clear that the election of the most representative end-members in the mixture is key to the desired result.

Classification by Spectral Unmixing



Classification by Spectral Unmixing

The reflectance value of each pixel is

$$r = M.f$$

where *r* is the reflectance in the pixel, *M* is a matrix which columns are the signatures of the selected end-members, and *f* is a vector representing the fraction of each end-member corresponding to the analyzed pixel.

If the matrix is not invertible, a pseudo-inverse shall be computed:

$$M^* = (M\,M^t)^{-1} M^t$$

which is a least squares fitted solution.

Classification by Spectral Unmixing

A vector of percentages

$$f' = M^{*}\, r$$

can be used for reconstructing the image (pixel by pixel) and obtaining from it the reflectance values

$$r' = M.f.$$

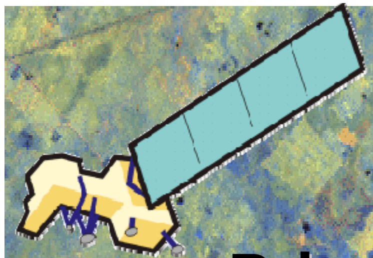
In such a way, the error of the method can be estimated by the quadratic difference

$$e = (r' - r)^2$$

Classification by Spectral Unmixing

Contingency table

Field Data Categories	Band Categories				Total
	1	2	3	4	
1	1	1	0	0	2
2	4	15	1	0	20
3	0	0	5	2	7
4	0	0	0	4	4
Total	5	16	6	6	33



Classification by Spectral Unmixing

Principal components analysis

Variable	Comp1	Comp2	% reconstruction of each variable in the plane
BAND 2	**- 0.69970**	0.18315	52.31
BAND 4	**0.73597**	- 0.16958	57.04
CHLOROPHILL.	**0.89717**	- 0.22452	85.53
TOTAL SOLIDS	**0.93425**	0.20324	91.41
FIXED SOLIDS	**0.89679**	0.21089	84.86
FILTERED SOLIDS	**0.77242**	0.48022	82.72
SECCHI DEPTH	**- 0.79546**	0.42759	81.55

Artificial Neural Network Models

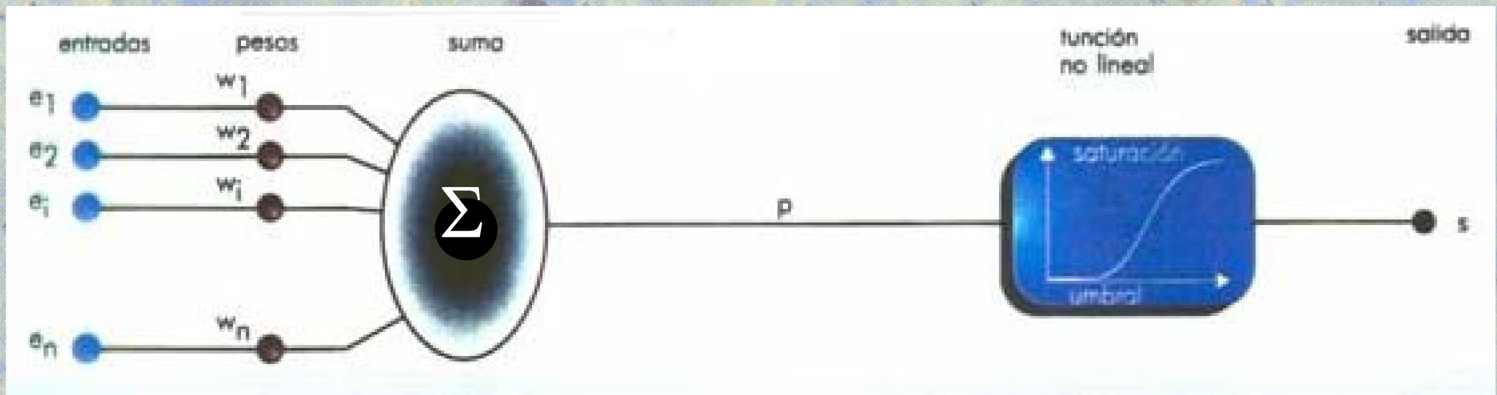
- An Artificial Neural Network is an approximation model of the “black box” type.
- It imitates the learning process of a human brain.
- They are adequate for complex systems that involve non-linearities
- They can handle large numbers of variables.
- They have great predictive capacity and can ignore intrinsic noise in measurements.

Artificial Neural Network Models

ARCHITECTURE of an ANN MODEL

Non-linear elements (neurons) forming layers.

Each neuron computes the weighted addition of its input values and generates an activation function which is a function of the inputs it has received.



A commonly used activation function is the logistic sigmoid function which has its range in the interval (0, 1) and is used to normalize the response of output nodes (neurons).

Artificial Neural Network Models

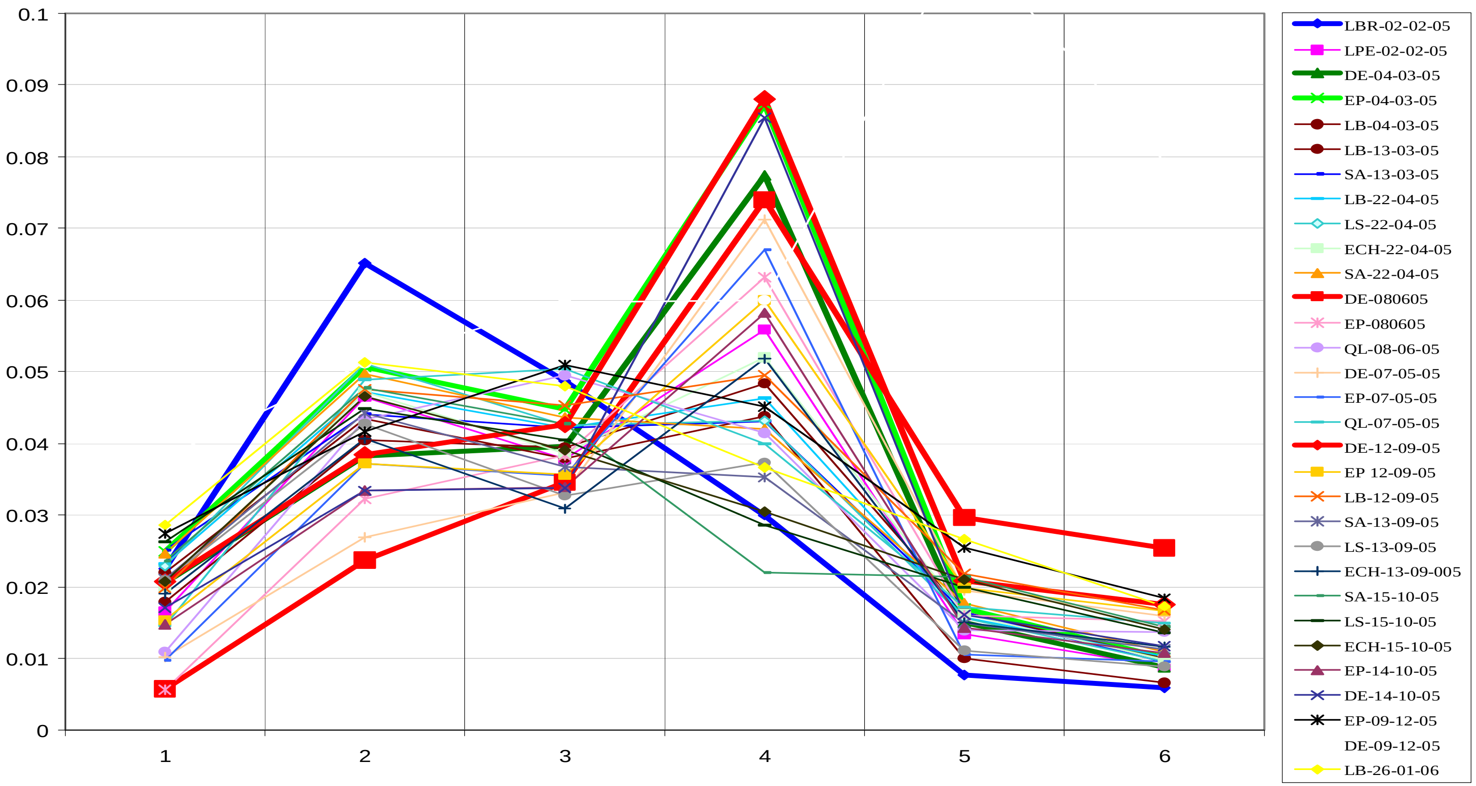
We use a “forward feed” ANN called Multilayer Perceptron and it is trained using a *Back Propagation (BP)* algorithm.

The ANN is fed with an input data set and the corresponding output.

First the input is given and the calculations through the network yield the output, then the error in the output is computed, and finally the weights in the network are updated.

Artificial Neural Network Models

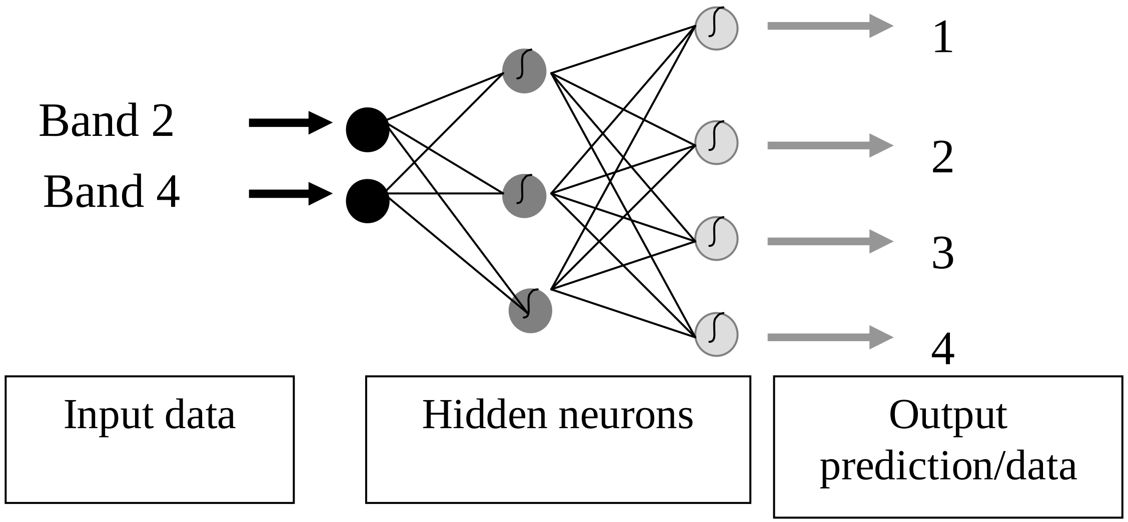
Automatic preprocessing of satelite images using classification of field data and spectral signatures



Spectral signatures of La Barrancosa (LB), Quilla Lauquen (QL), San Antonio (SA), La Salada (LS), El chifle (ECH), Del Estado (DE), La Brava (LBR) and El Paraíso (EP) at different dates.

Artificial Neural Network Models

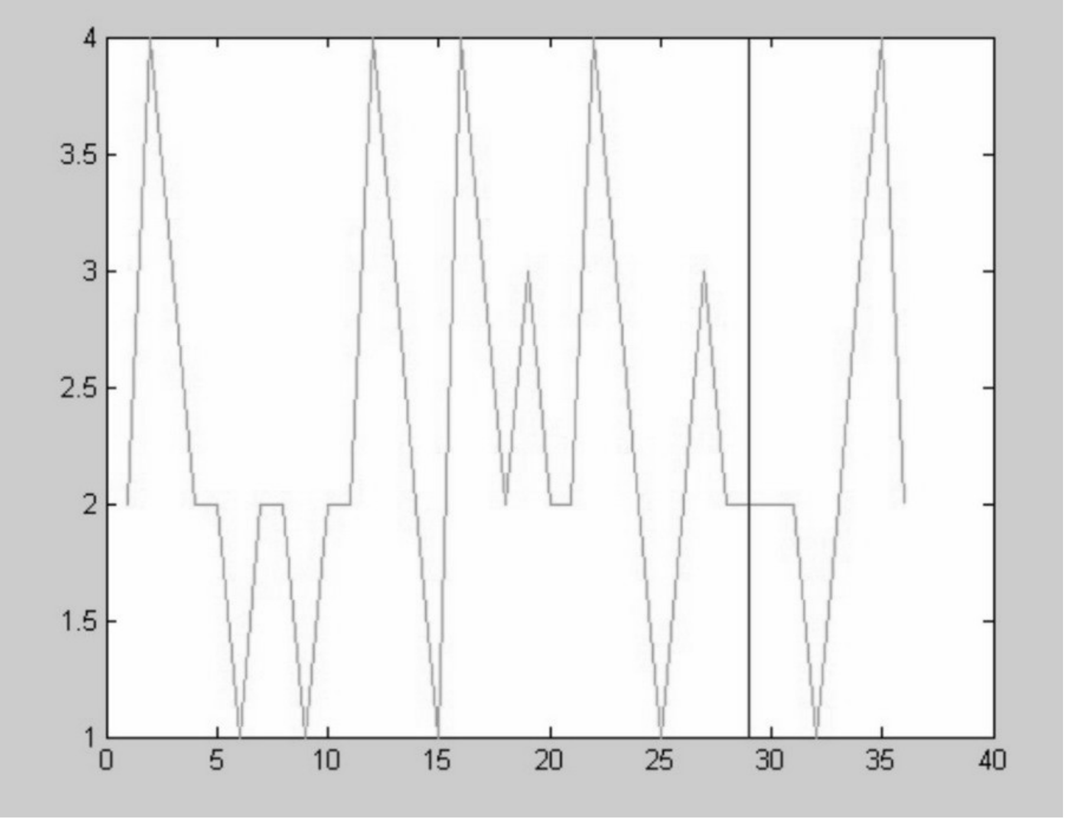
Construction of an ANN model for obtaining a ponderation of Bands 1 to 5 (visible and near infrared spectrum) of LANDSAT 5 TM and LANDSAT 7 ETM+



Classification architecture.

Artificial Neural Network Models

Clasification of shallow lakes based on their spectral signature as a function of their turbidity

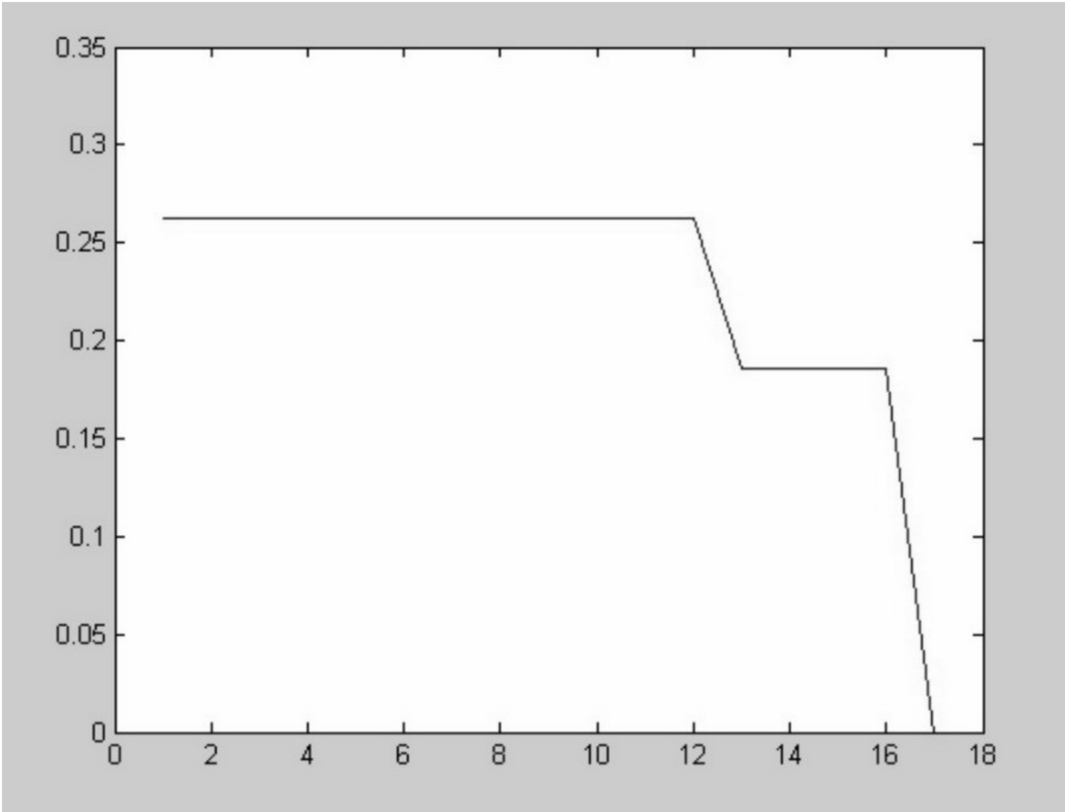


The predicted output is 100% accurate

Artificial Neural Network Models

METODOLOGÍA

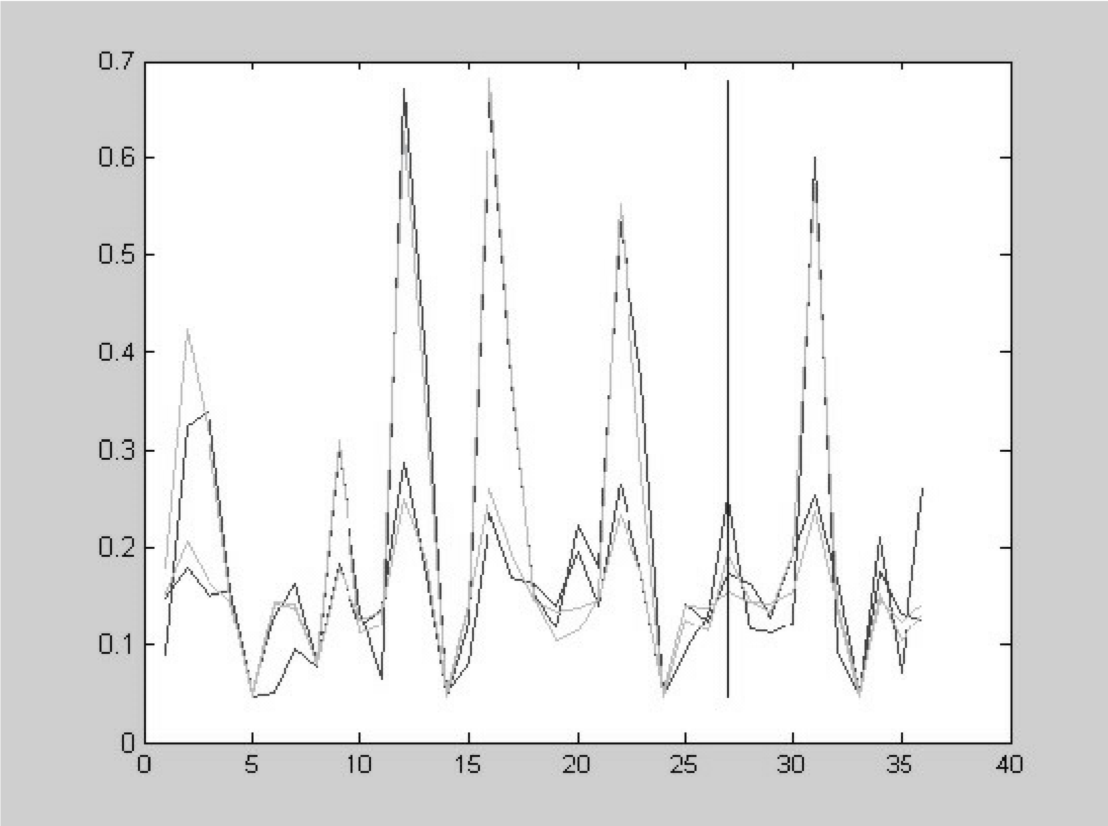
Clasification of shallow lakes based on their spectral signature as a function of their turbidity



Accuracy is obtained very fast

Artificial Neural Network Models

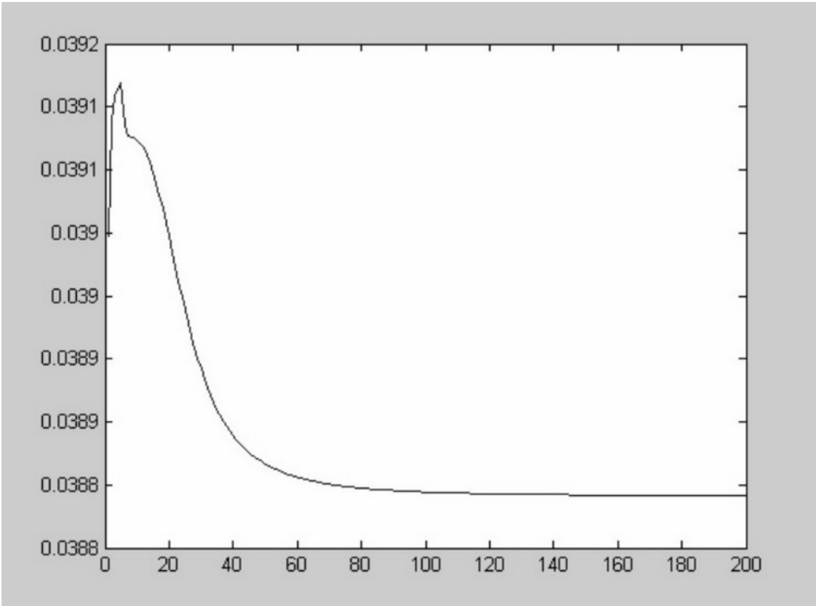
Determination of Total Solids and Chlorophyll-a

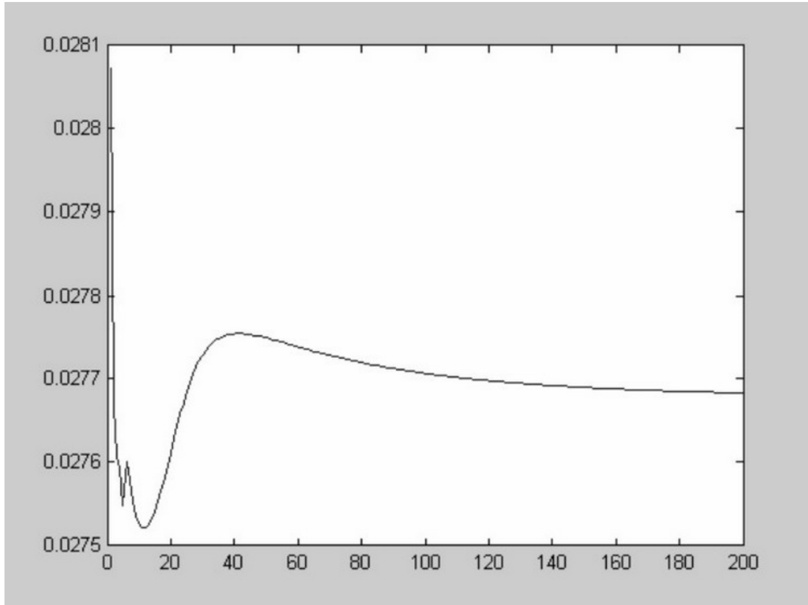


Total Solids (1/1000 mg/l) and Chlorophyll (1/1000 mg/m3) concentrations, when ANN runs are performed using both sets together, measured (black lines) and obtained from the ANN model (gray lines)

Artificial Neural Network Models

Determination of Total Solids and Chlorophyll-a

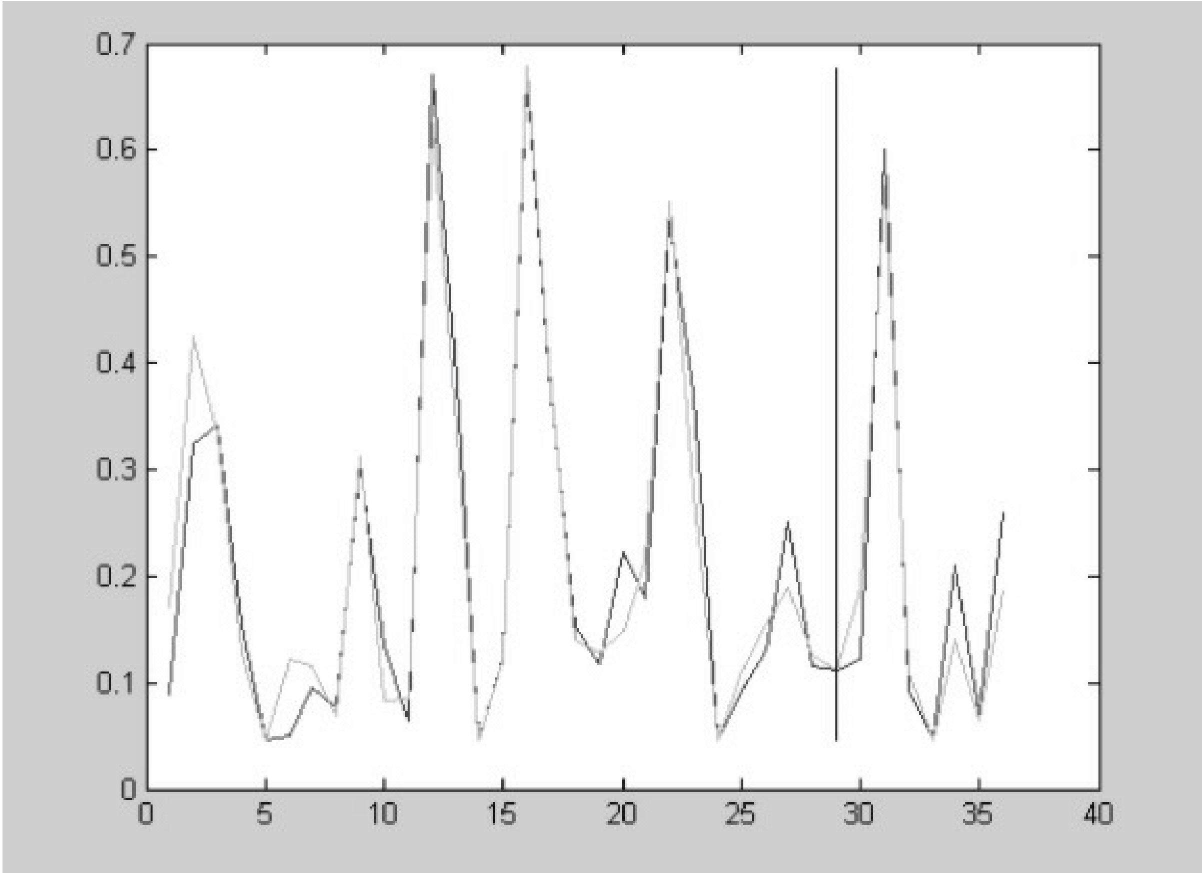




Learning and Predicting Errors for this ANN

Artificial Neural Network Models

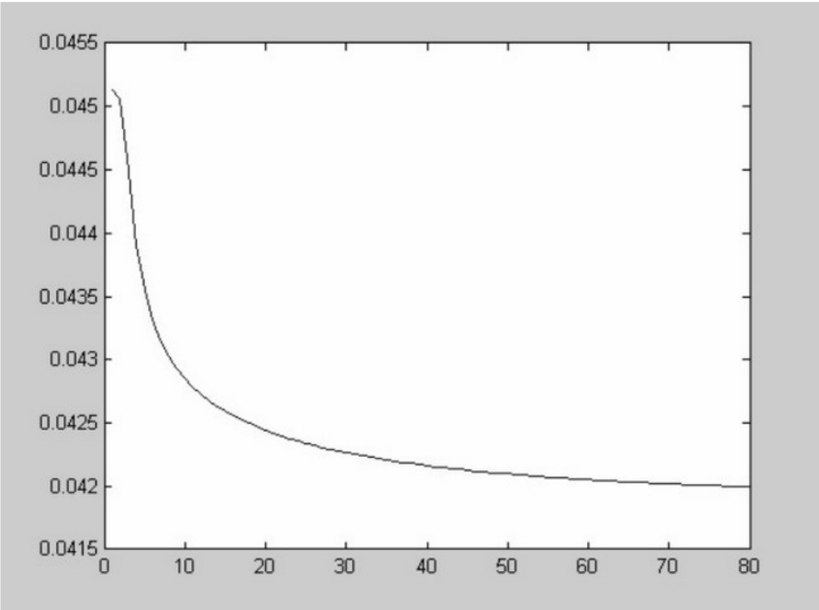
Determination of Chlorophyll-a concentrations

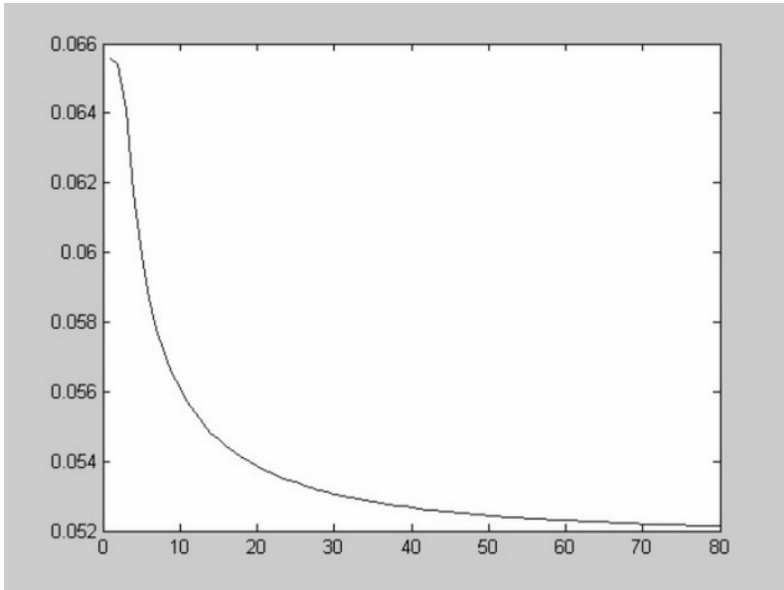


Concentrations of Chlorophyll (1/1000 mg/m3) measured (black) and obtained from the ANN model (gray)

Artificial Neural Network Models

Determination of Chlorophyll-a concentrations

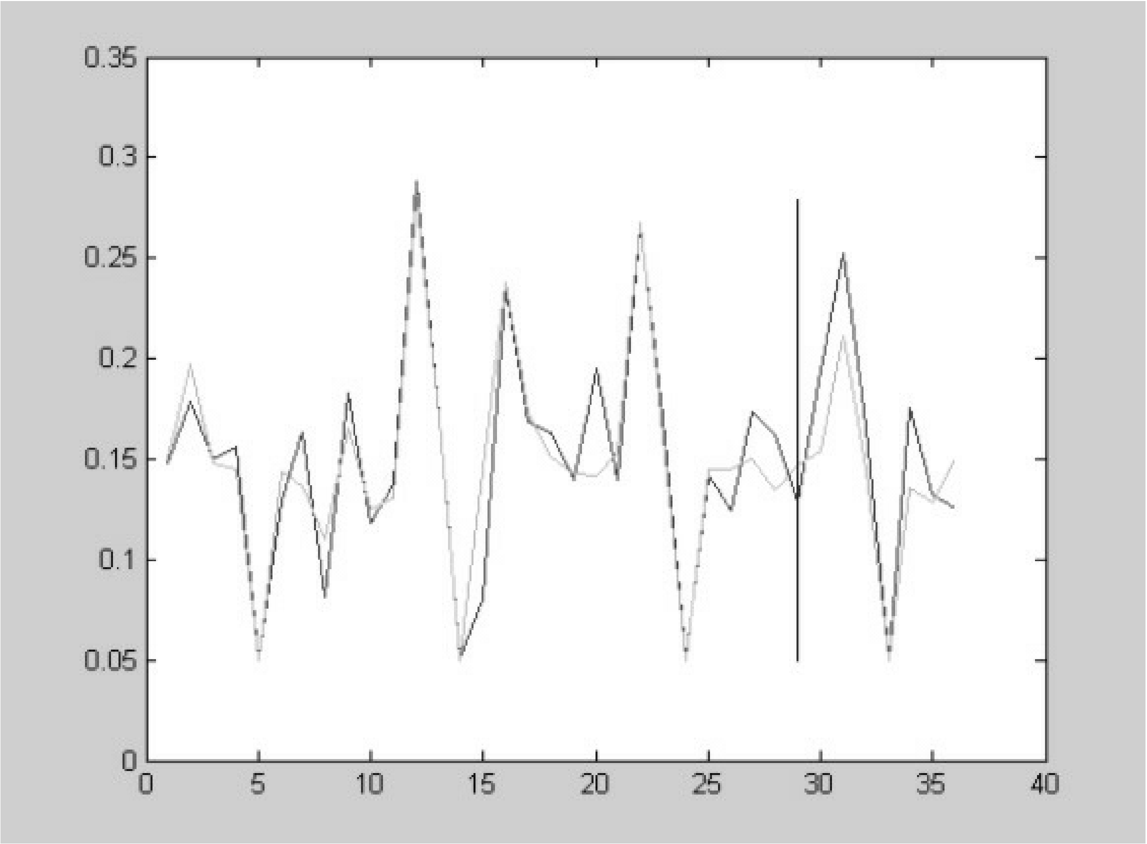




Learning and Predicting Errors for this ANN

Artificial Neural Network Models

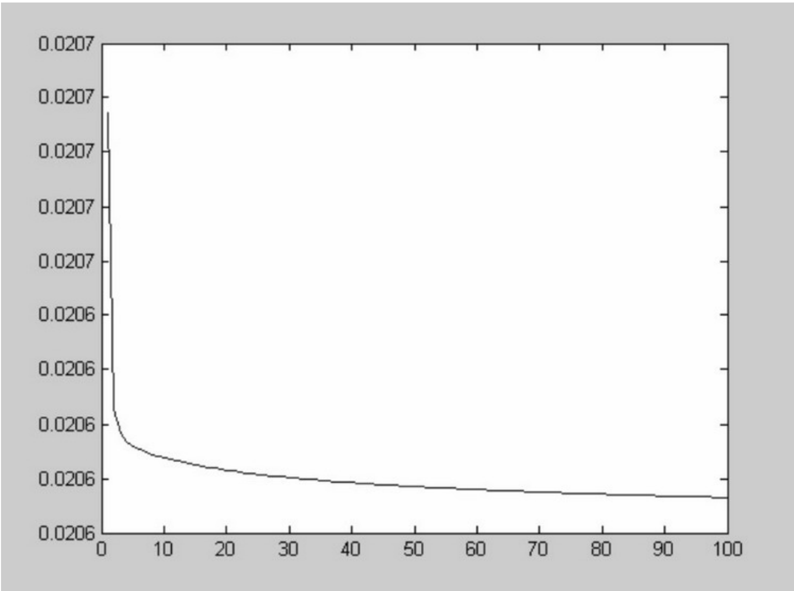
Determination of Total Solids concentrations

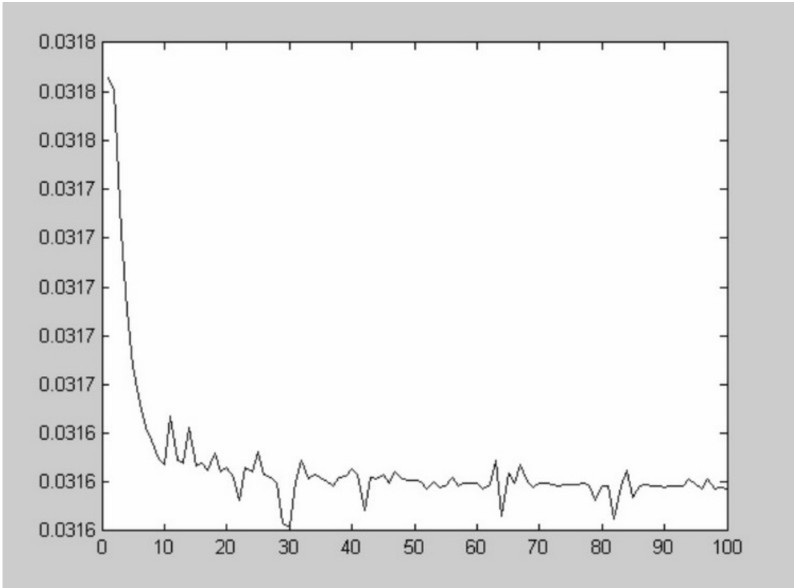


Concentrations of Total Solids (1/10000 mg/l) measured (black) and obtained from the ANN model (gray)

Artificial Neural Network Models

Determination of Total Solids concentrations





Learning and Predicting Errors for this ANN

Artificial Neural Network Models

Validation of results

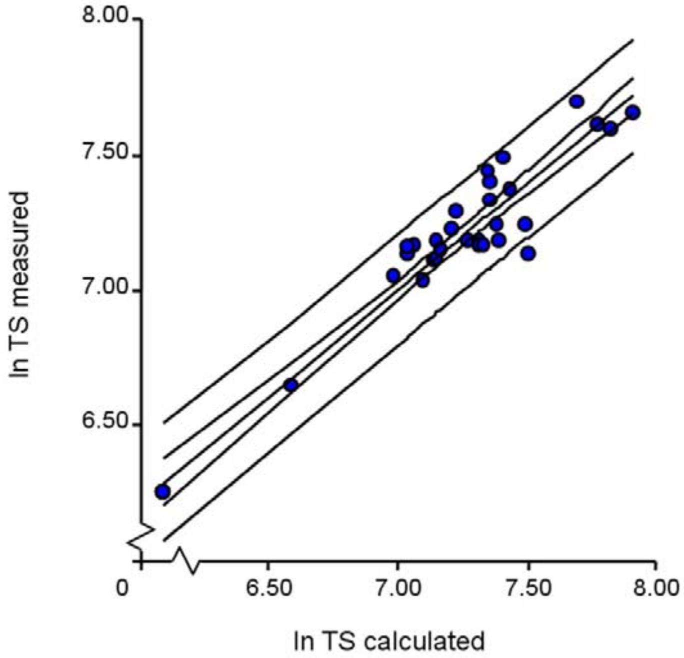
	Random Sample	La Barrancosa	San Antonio	Chifle – La Salada	Chifle – El Paraiso
Median Total Solids	1624 mg/l	1624 mg/l	1396 mg/l	1849-1249 mg/l	1849-1700 mg/l
Absolute learning error	200 mg/l	224 mg/l	216 mg/l	170 mg/l	156 mg/l
Absolute predicting error	320 mg/l	205 mg/l	217 mg/l	357 mg/l	821 mg/l
Mean square error	0.01	0.03	0.02	0.03	0.04
Determination coefficient	0.94	0.87	0.87	0.87	0.79

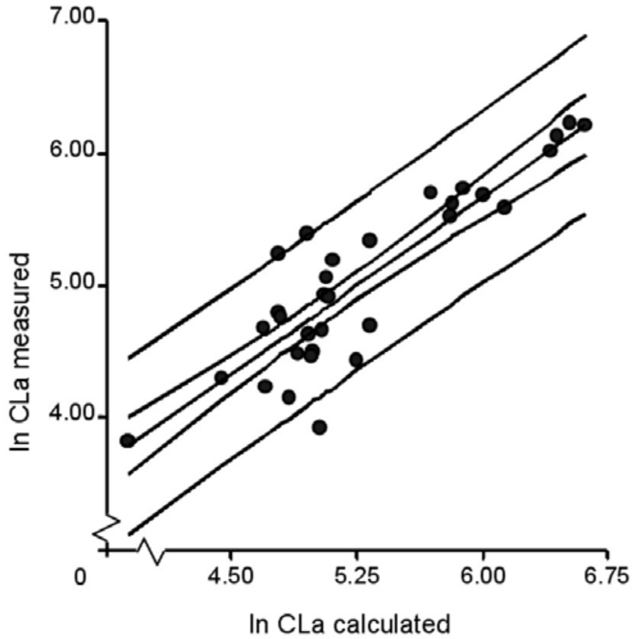
	Random Sample	La Barrancosa	San Antonio	Chifle – La Salada	El Paraiso
Median chlorophyll-a	153.5 mg/ m^3	95.7 mg/m^3	94.0 mg/m^3	216-132 Mg/m^3	369 mg/m3
Absolute learning error	42 mg/m^3	42 mg/m^3	42 mg/m^3	37 mg/m^3	45 mg/m^3
Absolute predicting error	52 mg/m^3	48 mg/m^3	63 mg/m^3	74 mg/m^3	182 mg/m^3
Mean square error	0.09	0.08	0.08	0.09	0.16
Determination coefficient	0.86	0.89	0.88	087	0.77

Artificial Neural Network Models

Validation of results

Regression analysis of measured and calculated total solids and chlorophyll-a with confidence and prediction bands





These mostly eutrophic and hypereutrophic lakes challenge the usual methodologies because of the influence that this characteristic has on the optic properties captured by the satellite sensors.

Spectral Unmixing has been widely applied to land cover analysis, but only recently has been used for water bodies.

Spectral Unmixing seems an adequate tool for classifying this type of shallow lakes.

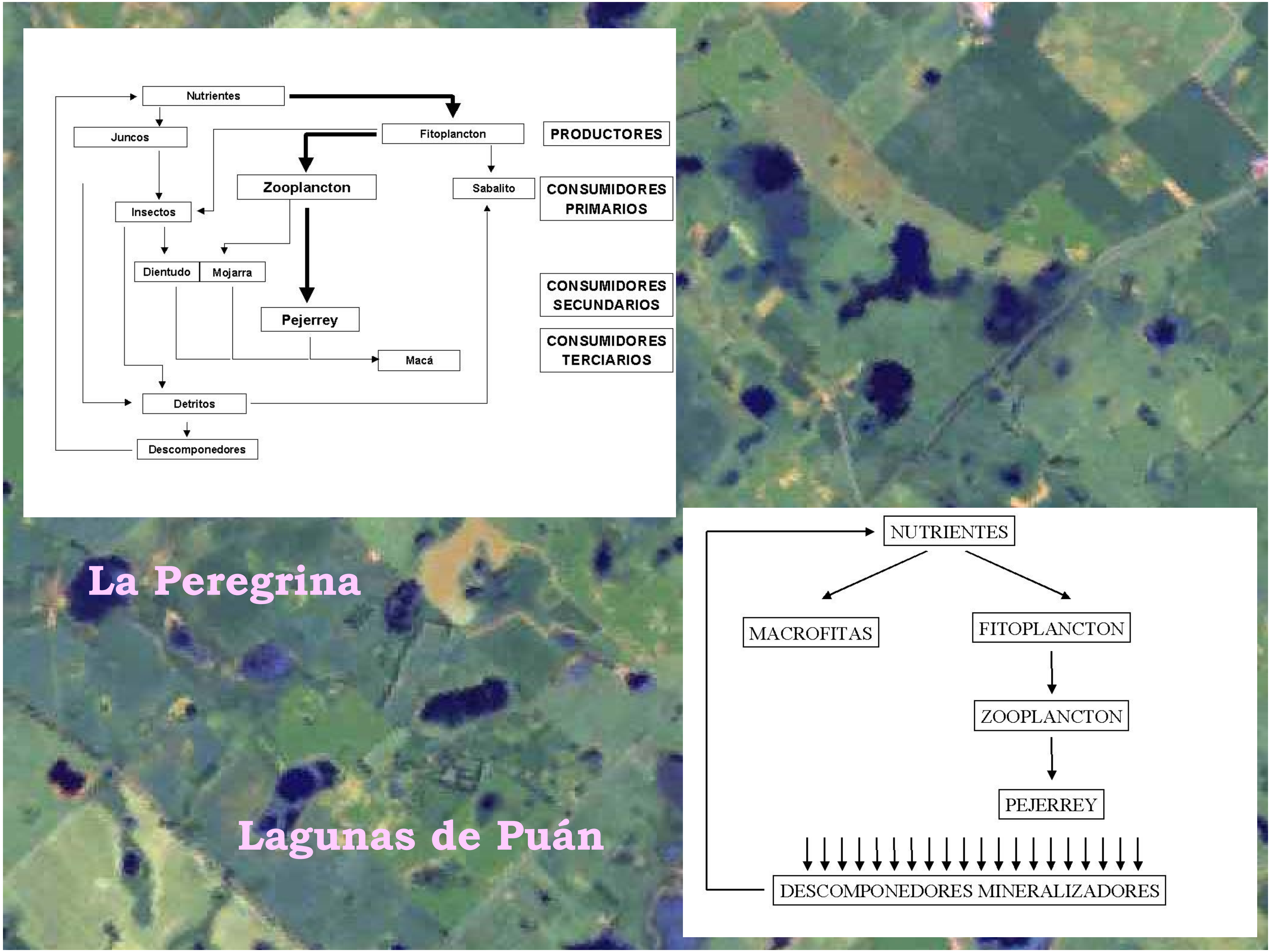
Most published research shows that ANN methods have been mostly developed for water bodies that exhibit chlorophyll-a concentrations below 100 mg/m3.

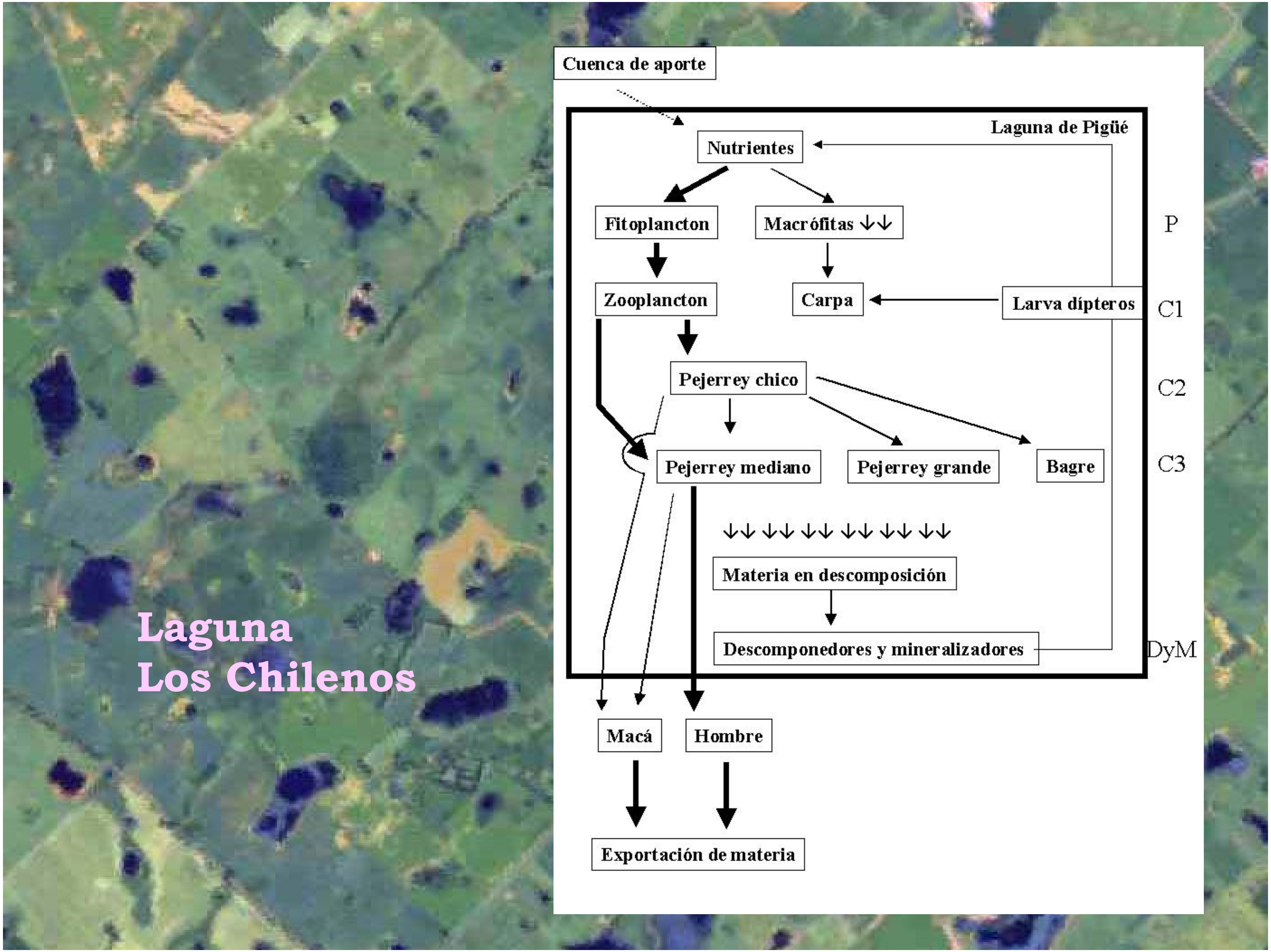
Our ANN models have proven to be very adequate for the classication of shallow lakes following their turbidity, yielding accurate output relative to the quantile probability distribution obtained from field data.

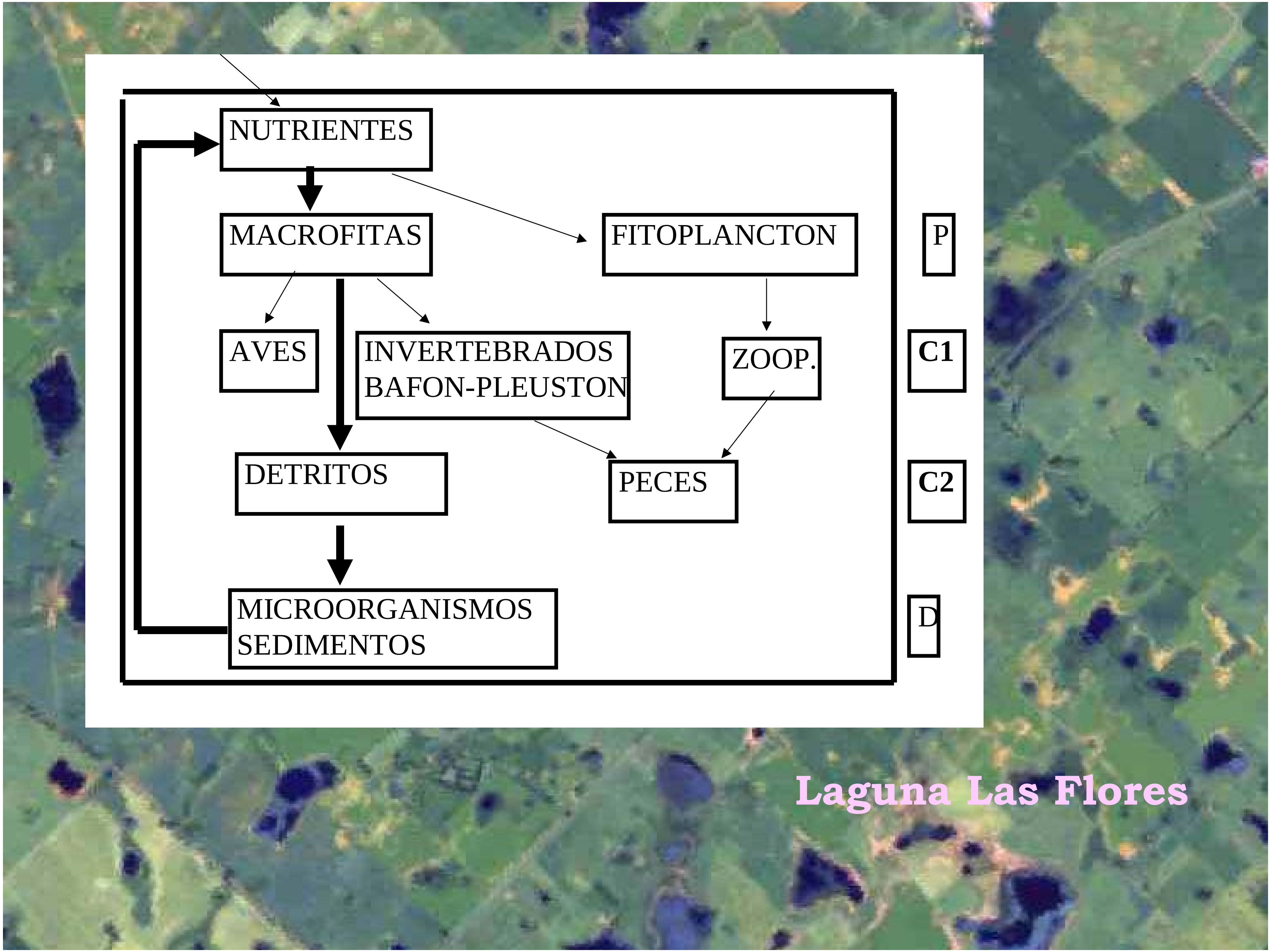
This methodology can be confidently used for classifying other shallow lakes of the region.

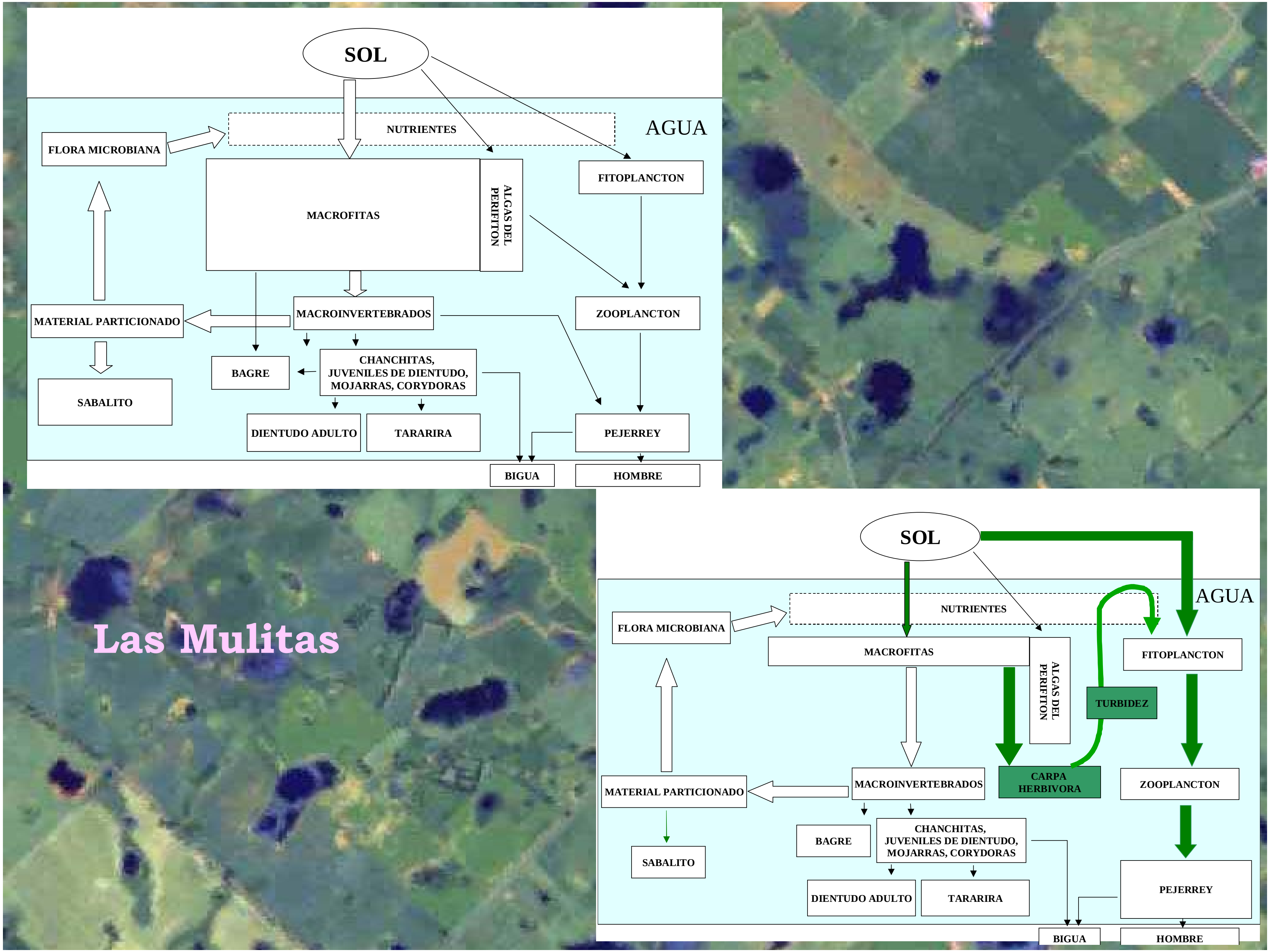
ANN models here developed seem capable of dealing with the mentioned wide range of concentrations with low error and good confidence values.


Thank you!
www.exa.unicen.edu.ar/ecosistemas/

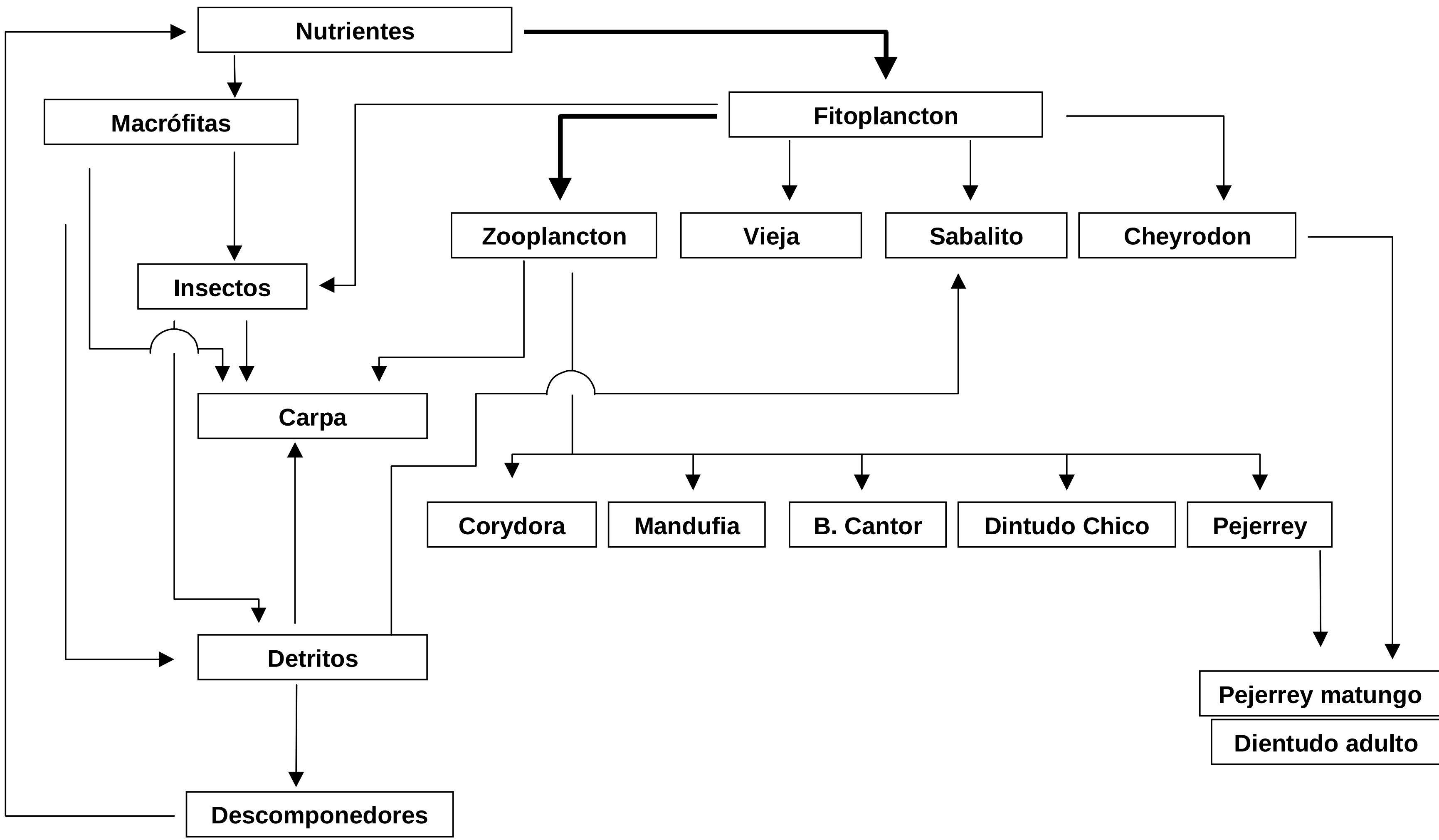

Nutrientes
Juncos
Fitoplancton
PRODUCTORES
Zooplancton
Sabalito
CONSUMIDORES PRIMARIOS
Insectos
Dientudo
Mojarra
CONSUMIDORES SECUNDARIOS
Pejerrey
CONSUMIDORES TERCIARIOS
Macá
Detritos
Descomponedores
La Peregrina
Lagunas de Puán
NUTRIENTES
MACROFITAS
FITOPLANCTON
ZOOPLANCTON
PEJERREY
DESCOMPONEDORES MINERALIZADORES


Laguna
Los Chilenos
Cuenca de aporte
Laguna de Pigüé
Nutrientes
Fitoplancton
Macrófitas ↓↓
P
Zooplancton
Carpa
Larva dípteros
C1
Pejerrey chico
C2
Pejerrey mediano
Pejerrey grande
Bagre
C3
↓↓ ↓↓ ↓↓ ↓↓ ↓↓ ↓↓
Materia en descomposición
Descomponedores y mineralizadores
DyM
Macá
Hombre
Exportación de materia


NUTRIENTES
MACROFITAS
FITOPLANCTON
P
AVES
INVERTEBRADOS
BAFON-PLEUSTON
ZOOP.
C1
DETRITOS
PECES
C2
MICROORGANISMOS
SEDIMENTOS
D
Laguna Las Flores


SOL
AGUA
NUTRIENTES
FLORA MICROBIANA
MACROFITAS
ALGAS DEL PERIFITON
FITOPLANCTON
MATERIAL PARTICIONADO
MACROINVERTEBRADOS
ZOOPLANCTON
BAGRE
CHANCHITAS, JUVENILES DE DIENTUDO, MOJARRAS, CORYDORAS
SABALITO
DIENTUDO ADULTO
TARARIRA
PEJERREY
BIGUA
HOMBRE
Las Mulitas
SOL
AGUA
NUTRIENTES
FLORA MICROBIANA
MACROFITAS
ALGAS DEL PERIFITON
FITOPLANCTON
TURBIDEZ
MATERIAL PARTICIONADO
MACROINVERTEBRADOS
CARPA HERBIVORA
ZOOPLANCTON
SABALITO
BAGRE
CHANCHITAS, JUVENILES DE DIENTUDO, MOJARRAS, CORYDORAS
PEJERREY
DIENTUDO ADULTO
TARARIRA
BIGUA
HOMBRE

Laguna de Monte



Laguna de Monte