Multitemporal approach for mapping shallow lakes in the context of large wetlands of South America floodplains

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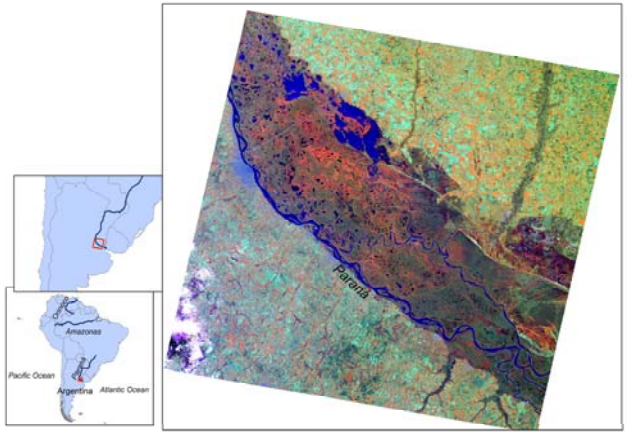
Framework

The largest wetlands in South America are associated with the floodplains of the big rivers such as Orinoco, Amazonas and Paraná.

One of the main features of these wetlands is the presence and the number of shallow lakes (**SL**) spread in a matrix of wetlands. **SL** perform a variety of important ecosystem services, such as habitat for freshwater aquatic plants and animals , spawning, breeding and shelter sites for fish, many of them of commercial interest.

Mapping the extents of **SL** is a basic practice for a better understanding of wetland dynamics and for the wetland ecosystem monitoring. A main limitation for mapping **SL,** lies in identifying the uncertain boundary that appears as a set of mixed pixels in images due to the fragmented nature of wetland cover types in the floodplains, as well as the true likely area occupied by the shallow lakes because of their spatial and temporal intrinsic variability.



Objective, data and methodology

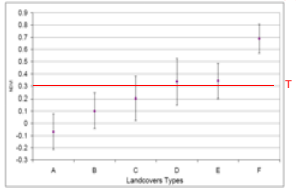
The objective is to identify and map shallow lakes (SL) from their surrounding wetlands in a floodplain , considering their spatial and temporal variability. The study area was set in the Lower Paraná River floodplain.

Our hypothesis is that SL show an increased frequency of flooding compared with the surrounding marshes.

DATA: Time series made by 77 scenes of historical Landsat 5 TM and 7 +ETM from 1987 to 2010. Path/Row: 226/83

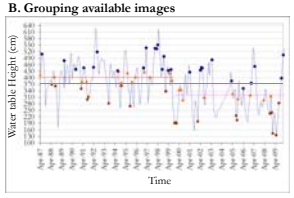
1. Building frequency from NDVI images

A. Extract a threshold NDVI value (T_{NDVI}). Descriptive statistics were analyzed in order to find a T_{NDVI} value, able to discriminate a pixel of water from its neighbors. Sampling of pixels was made on Landsat scenes that were simultaneous with field work. T_{NDVI} =0.3



A: Water with suspended sediments, **B**: water with content of phytoplankton, **C**: dominated by submersed macrophytes, **D**: clear water with emergent macrophytes, **E**: water full covered with emergent and floating macrophytes, **F**: Surrounding marshes.

B. Grouping available images



Three periods were defined acording to water level of Paraná River at Rosario Port:

1987-2010 **Complete (CP)**
1987-1999 **(Wet)**
2000-2010 **(Dry)**

(—) Mensual mean water level
(—) Mean water level 1987-2010
(—) Mean water level 1987-1999
(—) Mean water level 2000-2010

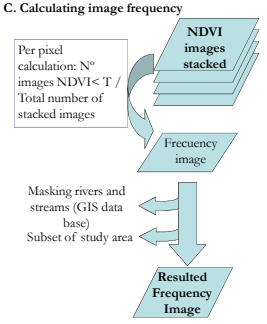
Landsat images with :
(■) **Low**, (▲) **Mean** and,
(●) **High** water level

12 sets of NDVI images were selected and stacked according to water level.

Threshold value was established as ± 30 cm around the mean value to define low and high water level.

Period	Set completed	N° of images
1987 - 2010 Complete (CP)	Total	77
	High water Level	34
	Mean water Level	15
	Low water Level	28
1987 - 1999 (Wet)	Total	42
	High water Level	17
	Mean water Level	15
	Low water Level	10
2000 - 2010 (Dry)	Total	35
	High water Level	12
	Mean water Level	11
	Low water Level	12

C. Calculating image frequency



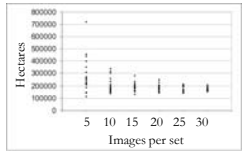
2. Classification of frecuency image

We classified each of the frequency image resulted according to flood frequency categories

Class	Flood Class	Range of Frequency
1	Surrounding Marshes	0 - 0.4
2	Eventually inundated	0.4 - 0.6
3	Frequently inundated	0.6 - 0.8
4	Permanently inundated	0.8 - 1

3. Sensitivity analysis

The estimated minimum number of randomly chosen images per set to reduce the dispersion of the results of the classification of shallow lakes, is between 15 and 20.



4. Consistency and Accuracy assessment

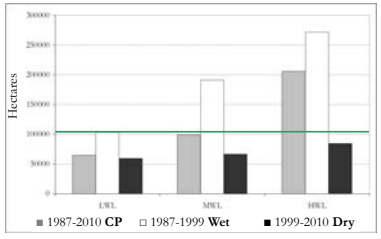
- We calculate the **kappa index** between all posible pairs of image sets, to evaluate the consistency of the results.
- Were perfomed an **accuracy assessment** on the final maps against two already published maps of shallow lakes for the same study area, obtained by :

Map 1) ISODATA classification of near and mid infrarred bands of the Landsat TM sensor, along with Wetness band (Tasseled cap) and NDVI from August 27, 2008 image corresponding to a regular hidrologic period - (Borro et al 2010)

Map 2) Classification by threshold of the absolute minimum values of NDVI, calculated from a time series made by 34 Landsat TM scenes from 1987 to 2010 (Borro et al 2009).

Results

•Area covered by water that is potentially shallow lake (SL)



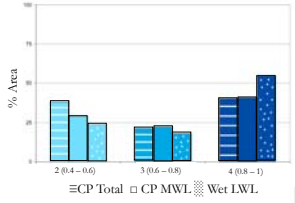
The area covered by water estimated for the set of image with low water level under the **Wet** period (**Wet LWL)** and Mean water level for the complete period (**CP MWL)** resulted similar to **CP Total**.
Looking at the **Dry** period, the area covered by water remain stable, but with a slight increment when **HWL** stack is used.

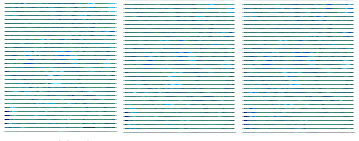
As expected, resulting area covered by water for **Wet** period is always higher than the others.

(—) **CP** Total= whole set of images, LWL= Low water level, MWL= Mean water level, HWL= High water level.

• Percentage of area occupied by flood classes for CP-Total, CP-MWL and WetLWL.

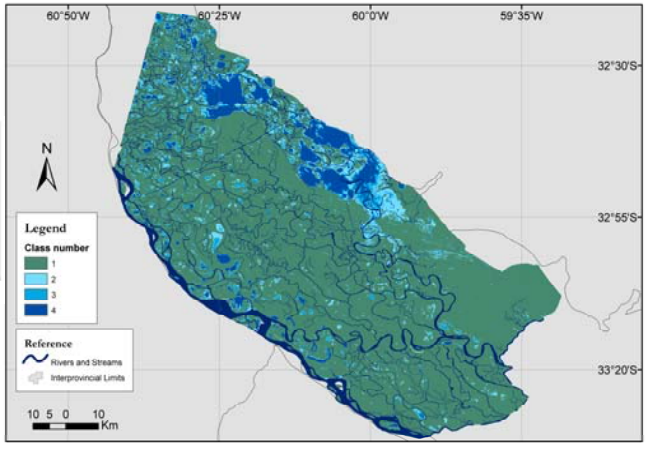
Although the area covered by water is almost the same for the three situations, the distribution of flood classes may differ. Anyway, in this case the differences are very slight.
Permanent water (Class 4) remains almost the same for **CP** being **Total** or **MWL**, but increase a litle for **Wet-LWL**.
Areas eventually flooded (Class 2) show major diferences, resulting higher considering **CP-Total** period.

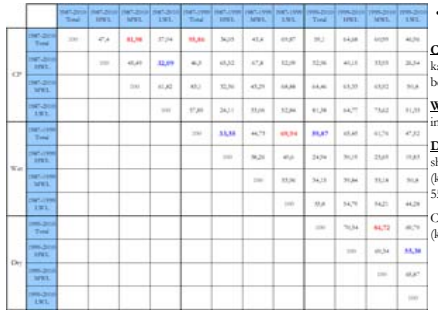




Area of Shallow Lakes

Estimated from 77 images from 1987 to





- **Consistency analysis**

Cross tabulation of Kappa index for the sets of images analyzed

Complete period 1987-2010 (CP). The **CP** analyzed shows an intrinsic variability. The mayor kappa index (81.98%) is between the **Total** and **MWL** set of images. The minor kappa index is between **HWL** and **LWL** (32.09%).

Wet Period 1987-1999 (Wet). The most similar results are obtained from **Total** and **LWL** set of images (kappa 69.94). The biggest differences are between **Total** and **HWL** (kappa 33.55%).

Dry Period 2000-1910 (Dry). The dry period shows relatively stable thus kappa index in general show high values. As expected, the most similar results is obtained between **Total** and **MWL** (kappa 84.72%, while the highest difference is obtained between **HWL** and **LWL** (kappa 55.38%).

Comparing the **Total** sets, results from **CP** and **Wet** period set show the highest similarity (kappa 95.86). On the other hand, **Wet** period vs **Dry** period show low similarity (kappa 59.87))

•**Accuracy assesment**

	CP Total	CP MWL	Wet LWL
Map 1	70,25	69,5	64,6
Map 2	70,52	69,29	65,02

The kappa index for the 3 sets analized show high similarity with the **Map 1** and **2**

Borro, M.M.; Salvia, M.M.; Minotti, P.G.; Puig, A.; Karszenbaum, H. y Kandus, P. Primeros resultados de la clasificación de lagunas someras en la Región del Delta del Paraná bajo un enfoque ecohidrogeomórfico. 2009. Poster. II Jornadas Argentinas de Ecología de Paisajes. Córdoba, Argentina.
Borro, M.M.; Morandeira, N. S.; Salvia, M.M.; Minotti, P. G.; Puig, A.; Karszenbaum, H. y Kandus, P.Las lagunas de la planicie aluvial del Delta del Río Paraná: clasificación multitemporal e integración con datos limnológicos. 2010. Azul, Buenos Aires, Argentina. Exposición Oral. 1° Congreso Internacional de Hidrología de Llanuras.