Assessing optical earth observation systems for mapping and monitoring temporary ponds in arid areas

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Title

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Abstract (100-150 words)

Remote sensing methods for locating and monitoring temporary ponds over large areas in arid lands were tested on a study site in Northern Senegal. Three main results are presented, validated with field data and intended to highlight different spectral, spatial and temporal characteristics of the methods: 1) Among several water indices tested, two Middle Infra-Red-based indices (MNDWI – Modified Difference Water Index and $NDWI_2$ – Normalized Difference Water Index) are found to be most efficient; 2) an objective method is given prescribing the necessary sensor spatial resolution in terms of minimal detected pond area; and 3) the potential of multi-temporal MODIS imagery for tracking the filling phases of small ponds is illustrated. These results should assist in epidemiological studies of vector-borne diseases that develop around these ponds, but also more generally for land and water management and preservation of threatened ecosystems in arid areas.

Keywords: Remote sensing, Monitoring, Temporary ponds, Water indices, Arid areas.

1.   Introduction

In West Africa, and particularly in the semi-arid Sahel region, ponds and lakes play a crucial role for the local population and their livestock (Diop, 2007). Temporary water bodies are often the primary water supply for human and animal consumption, along with bores and wells that are periodically made available by the local or national authorities (Diop et al., 2004). Open water surfaces also enable vital ecological functions and provide the necessary natural habitats for a wide range of fauna. However, these are also sites with dense human and livestock populations, which favors the development and transmission of infectious and parasitic diseases. The biological diversity and resources of these fragile aquatic ecosystems are subject to various natural (recurrent drought) or anthropogenic (overexploitation, dams, pollution, drainage) threats that also need to be monitored. However, it is considered particularly challenging to inventory these water bodies as they are generally small, numerous, temporary, and spread over large and often poorly accessible areas.

Data acquired by Earth Observation systems covering a wide range of spectral, spatial, and temporal characteristics can be used for locating these ponds over large areas. For instance, the Near Infra-Red (NIR) band is theoretically well-suited for detecting open water surfaces from optical images, due to the strong water absorption in the NIR range (Verdin, 1996). However, because of some complicating water characteristics such as turbidity and/or the presence of aquatic vegetation (seaweed, duckweed, and others), the NIR band alone is not sufficient to properly distinguish open water surfaces (Puech, 1994). Indices were therefore developed combining the NIR band with other bands, such as the Normalized Difference Water Index as defined by Gao et al. (1996) ($NDWI_1$) and the Normalized Difference

Water Index as defined by Mc Feeters et al (1996) ($NDWI_2$). The former is a combination of NIR and Green (G) bands, while the latter combines NIR and Middle Infrared (MIR). The Normalized Difference Vegetation Index (NDVI) initially defined for vegetation studies (Townshend, 1986; Tucker, 1979) was also proven useful for detecting water and silt-laden open water from lateritic soils (Caloz et al., 1996). Lastly, the Modified Normalized Difference Water Index (MNDWI) was derived from the $NDWI_2$ by the use of MIR instead of NIR (Xu, 2006). The negative of the MNDWI has also been used in other studies, and is called the Normalized Humidity Index in (Clandillon et al., 1995) or Normalized Difference Pond Index (NDPI) in (Lacaux et al., 2007).

A method using NDVI and $NDWI_2$ indices was developed by the Global Environment Monitoring Unit of the European Joint Research Centre to map temporary ponds of about 100 ha in size in Sahelian areas with SPOT4-Vegetation (Haas et al., 2006). Puech (1996) showed that SPOT4-XS images with 20 m pixel resolution could be used for estimating pond areas (> 10 ha) in Niger with 95% accuracy, and their water volume with 70% accuracy. Using high spatial resolution data from SPOT5-HRG (10 m pixel resolution), Lacaux et al (2007) proposed the NDPI to detect small ponds of 0.5 ha.

Several studies have also reported the potential for producing time series images by coarse-scale satellite sensors like AVHRR (Advanced Very High Resolution Radiometer), MODIS (Moderate Resolution Imaging Spectroradiometer), and SPOT-Vegetation for vegetation monitoring (Beck et al., 2006; Boles et al., 2004; Maignan, 2008; McCloy and Lucht, 2004). Nevertheless, there are relatively few such studies on water body monitoring, as most of them monitor large water areas and are concerned with either flood monitoring (Barton and Bathols, 1989; Sandholt et al., 2003) or water storage in large lakes (Dingzhi P.

et al., 2005). The spatio-temporal dynamics of large water bodies can be monitored every 10 days using SPOT-Vegetation images time series (Haas et al., 2006), whereas the follow-up of small ponds derived from high spatial resolution images was only possible with 5 images/year (Lacaux et al., 2007).

When facing the problem of detecting and monitoring temporary ponds over large areas, the task of choosing among different remote sensing options in terms of spatial and temporal resolutions, spectral indices, or methodological approaches can be quite challenging. A trade-off between spatial and temporal resolutions is often inevitable, but can be based only on *a priori* reasoning due to the lack of appropriate comparative studies. The objective of this study is to address this issue by reviewing available methods for the selection of optical sensors to detect, map, and monitor water bodies in arid areas. Methods built on radiometric, spatial, and multi-temporal characteristics are applied using different optical remote sensing datasets from the same study area, which is representative of the West African Sahel region, and then comparatively assessed.

2. Study area and data

Study area. The study was conducted within an area of approximately 11x10 km around the village of Barkedji (15.22° N, 14.86° W) in North Senegal (Figure 1). Located in the Ferlo Valley, the study area is characterized by a complex and dense network of ponds that are filled during the rainy season (from July to mid-October). These temporary ponds provide water to semi-nomadic and nomadic populations that herd their flocks on the surrounding arid lands. The arid climate causes the water level of these ponds to fluctuate and decrease from July to October, via infiltration favored by sandy-loam soil, high

evapotranspiration, and human and animal consumption (Diop et al., 2004). All ponds in the study area, except the large Barkedji pond, dry out during the dry season (Figure 1).

<mark>*(Figure 1 here)*</mark>

Pond locations. In total, 98 ponds were located using a Global Positioning System receiver (GPS), then surveyed and described in detail in terms of water quality and vegetation type (September 2006). The GPS points collected at the pond boundary were later manually relocated to the center of the pond by photo-interpretation, using a very-high spatial resolution Quickbird image (see the remote sensing data section). This field survey showed that most of the ponds in the study area are small ponds (33% of ponds with an area less than 1000 m^2 and 64% with less than 2600 m^2), with the smallest covering only 74 m^2 and the biggest being the Barkedji pond with ~347,400 m^2.

Hydrological and meteorological data. We used water height data from the 2001 and 2002 rainy seasons (July – December), collected daily from water level meters placed at the center of three ponds: Mous, Furdu and Barkedji (Figure 1). Rainfall data was collected daily during the same time period from a rain gauge located in the village of Barkedji.

Remote sensing data. Optical Earth Observation System (EOS) sensors data with different spectral and spatial resolutions were acquired between 2001 and 2005 (see Table 1). Quickbird and Landsat Enhanced Thematic Mapper (ETM+) images were acquired during the rainy season in order to correspond with the time period of the pond location ground survey. Then 16-day composite images of NDVI (MOD13Q1/V05) were acquired for the period corresponding to the hydrological data survey (rainy seasons 2001 and 2002). We verified the homogeneity of the acquisition dates within our study area using the "250m 16 days composite day of the year" product. As a result, 2 of the 24 initially selected MODIS

NDVI composite images were removed from the analysis because the NDVI values were acquired on different days.

<div align="center">*(Table 1 here)*</div>

3. Method

3.1 Spectral analysis

We used the ETM+ image (radiance values) to assess the capacity of different spectral indices to correctly map the ponds within our study area. Indeed, with six spectral bands, the ETM+ sensor enabled us to compare the main water indices described in the scientific literature (Table 2).

<div align="center">*(Table 2 here)*</div>

The 98 GPS-located ponds were used as ground-truth reference ("pond pixels"). One hundred additional pixels were randomly selected outside of the ponds ("non-pond pixels") using Geographic Information System (GIS) functionalities (GIS software: ESRI ArcGIS^{TM}).

The predictive accuracy of the indices was assessed using the ROC (Receiver Operating Characteristic) curve method (Park et al., 2004). The ROC curve represents variations in the sensitivity (% of pond-pixels properly classified) and the specificity (% of non-pond pixels properly classified) of an index with varying threshold-value. The AUC (Area Under Curve) of the ROC curve and its 95% confidence interval was calculated for the four indices. The greater the AUC, the more discriminating the index, is and the closer the predictions are to the observed data.

We completed this analysis by studying the spectral signatures of the primary land cover types represented in the study area. The values of the four water indices were extracted

from pixel samples of water, water colonized by aquatic vegetation, active vegetation, and bare soil and lateritic soil.

3.2 Spatial resolution analysis

The impact of spatial resolution on pond detection was studied using the Quickbird image. The initial radiance image was gradually degraded from high (pixel size of 2.44 m x 2.44 m) to low spatial resolution (1 km x 1 km) by factors of 2. We obtained 159 images in order to create a continuous spatial resolution gradient. NDVI was derived from the NIR and R bands (in radiance unit) from each image. The ponds were detected in each image by radiometric thresholding. A threshold value of 0.041 was chosen according to the spectral analysis results. For each spatial resolution, we then calculated the number of detected ponds and their mean area.

Finally, the Landsat image and a MODIS image (10 August 2005) were processed to detect the water bodies with the same method (NDVI / threshold 0.041) in order to compare the results obtained from the Quickbird image when resampled at 30 m and 232 m, with results from real EOS data.

3.3 Times series analysis

The ability of optical EOS to monitor temporary ponds was assessed using a time series of MODIS NDVI images. Due to their simplicity, we used the MODIS NDVI layer. NDVI mean values were extracted within a 3x3 pixel window at the Mous, Furdu and Barkedji ponds (Figure 1) to avoid geometric transformation uncertainty. Because of the MODIS spatial resolution and the small size of the ponds, this value reflects the state of the water area and of its surrounding environment (*i.e.,* vegetation and soils).

To evaluate and quantify the relationship between NDVI and the water heights time series, we used an empirical temporal cross-covariance (see Appendix), which is useful for comparing two temporal series with different temporal steps (*i.e.,* 16 days for the MODIS NDVI data, 1 day for the water height measurements). The temporal cross-covariance was computed for each pond between the MODIS NDVI and the water height original time series, for Δt ranging from -40 to +40 days with a temporal step of 4 days. To test the statistical significance of the results, we followed a Monte-Carlo procedure, independently randomizing the values of the temporal series 1000 times. The cross-covariance was computed on each simulated dataset to obtain 95% confidence intervals of cross-covariance value under the assumption of randomness. The statistical analysis was performed using R (R Development Core Team, 2006).

We applied this analysis to the entire time series (from July to mid-October) and to time series corresponding to only the rainy season (from July to mid-September) in order to exclude the emptying phase of the ponds. Indeed, since NDVI indicates the chlorophyll activity of the vegetation, the NDVI index may remain high at the end of the rainy season even while precipitation is rare and ponds are empty (Schmidt and Karnieli, 2000).

Finally, we used the same test to evaluate the relationships between cumulative rainfall and water heights and between cumulative rainfall and MODIS NDVI values.

4. Results

4.1 Spectral analysis

According to the ROC analysis, the two indices using the MIR band, *i.e.,* the MNDWI and the $NDWI_1$, are the more discriminating indices for the detection of water bodies, with

AUC values of 0.90 and 0.77, respectively (Figure 2). The two other spectral indices, the NDVI and the NDWI$_2$, are less appropriate according to our study area, with AUC values of 0.60 and 0.46, respectively.

(Figure 2 here)

Studying the spectral signatures of the primary land cover types allowed us to interpret these results, highlighting confusion between some land cover types (Figure 3). The MNDWI appears to be the most efficient at isolating free water areas, which return positive MNDWI values whereas all others land cover types return negative values. However, this index does not distinguish water with vegetation from vegetation alone.

The NDWI$_1$ allows proper distinction of bare and lateritic soils from other land cover types, but does not separate water bodies from vegetation areas.

The NDVI has a low level of free water detection, often confusing bare soils with free water. The fact that most water ponds are turbid in the Sahel region leads to misinterpretation of turbid water bodies as bare soils.

Lastly, the NDWI$_2$ appears to be inadequate for discriminating between the different land cover types in our study area, as they all return very similar index values.

(Figure 3 here)

4.2 Spatial resolution analysis

As expected, the results of the spatial resolution analysis showed that higher image resolution corresponded to a higher number and smaller size of detected ponds (Figure 4). The shape of the curve highlights a quasi-linear relationship between the spatial resolution and the size of the detected ponds for ponds less than 26500 m^2 in size. Above this

1

threshold value, the size/resolution relationship is more difficult to interpret, since there are very few large ponds (2) within the study area.

The number of ponds detected using real EOS data from Landsat and MODIS imagery (32 and 3, respectively) were in agreement with the number of ponds detected using the resampled Quickbird images at 30 and 232 meters (31 and 1, respectively).

(Figure 4 here)

4.3 Times series analysis

A significant correlation was observed between the MODIS NDVI series and the water heights measured in the field for the three ponds of Mous, Furdu and Barkedji (Figure 5). The cross-covariance maxima (Barkedji: *cov*=0.64, p<0.05; Furdu: *cov*=0.71, p<0.05; Mous: *cov*=0.55, p<0.05) were observed for different time lags (Barkedji: Δt=+6 days; Furdu: Δt=-6 days; Mous: Δt=-2 days), indicating that MODIS NDVI increases a few days before the rise in water height in the smaller ponds (Furdu and Mous), whereas that relationship is inverse for the larger pond (Barkedji pond).

When the emptying phase water height values are removed from the analysis, the results show a higher correlation between MODIS NDVI values and water heights for the Furdu and Mous ponds (Furdu: *cov*= 0.81, p<0.05 and Mous: *cov*=0.80, p<0.05), and no change for the Barkedji pond (*cov*=0.61, p<0.05) except for a shortened time lag.

On the other hand, water heights are poorly correlated with cumulative rainfall data (Barkedji: *cov*= 0.25, p<0.05; Furdu: *cov*= 0.29, p<0.05; Mous: *cov*=0.40, p<0.05), with short time lags ranging from − 2 days to − 10 days, meaning that the increase in water height occurs a few days after the increase in rainfall.

(Figure 5 here)

5. Discussion

Unlike a review article, the results presented above pertain to one particular study area for which significant baseline, or ground-truthing, work had also been carried out. This ensures that different methods or indices can be compared directly for identical situations, and their relative performances can thus be quantitatively assessed. In this way, the present work brings useful new information that may help substantiate the choice of an appropriate remote sensing option for monitoring water bodies in arid areas.

The study on spectral indices showed that the indices using the MIR band as the MNDWI (Xu, 2006) and the $NDWI_1$ (Gao, 1996; Hardisky, 1983) are the most efficient indices for detecting water bodies in arid areas. According to our results, the MNDWI is particularly suited to the detection of free water (Xu, 2006). Neither of those two indices enables the distinction of aquatic vegetation from the vegetation surrounding the ponds. However, this may not limit the use of remote sensing for the detection of water bodies in Sahel areas, as in such areas ponds are typically surrounded by land with sparse vegetation cover, which is a symptom of continuous over-use, trampling, and overgrazing. The two other indices tested in our study, the NDVI (Townshend, 1986; Tucker, 1979) and $NDWI_2$ (McFeeters, 1996), showed a low capacity for detecting free water bodies at the spatial resolution of Landsat ETM+. Nevertheless, higher scores might be expected if these indices were to be derived from higher spatial resolution data.

The results of the spatial analysis highlighted the strong impact of the spatial resolution on the characteristics of the detected ponds. Moreover, the results lead to a recommendation in terms of sensor system choice for a given minimal pond area. According to our results (see

Figure 4), Very High Spatial Resolution imagery such as Quickbird, Ikonos and SPOT5 sensors may be useful to detect small ponds with an area of as low as 70 m² (one pond in our study area). High-resolution satellite data such as SPOT 4-HRVIR and Landsat ETM+ allows the identification of ponds with sizes ranging from about 1100 m² to 2500 m² (27 % ponds). Medium spatial resolution sensors like MODIS allow the detection of ponds greater than 1,700,000 m² (3). Finally, the SPOT Vegetation sensor, with a pixel size of 1 km x 1 km, is found inappropriate for identifying the ponds in the study area.

Since optical EOS allows the detection of water bodies in arid areas at different spatial resolutions as assessed in the previous section, the monitoring of the ponds' temporal dynamics may be performed using the same type of imagery. Nevertheless, because of a common compromise between EOS spatial and temporal resolutions, high spatial resolution sensors may only provide a punctual information, such as about 5 images/year for one given site covered by SPOT5-HRG data (Lacaux et al., 2007).

Thus, the utility of medium spatial resolution image time series for monitoring the hydrologic dynamics of water bodies in arid areas with a high temporal frequency appears very promising. Our results show a strong correlation between MODIS NDVI values and water heights collected in the field. Further, the MODIS NDVI time series data seem to be efficient at identifying the filling phases of the ponds. Indeed, the statistical relationship between MODIS NDVI and the water height time series was strengthened by removing all water height data corresponding to the emptying phase of the ponds.

These results highlight the added value of using remotely sensed data over meteorological data for monitoring ponds in arid areas. The shortened time lag (-2 to -6 days) between the NDVI value and the water height is in agreement with hydrological studies showing that

the filling of ponds in arid areas is mainly due to water streaming, and not to direct rain contribution (Desconnets et al., 1993) In the Sahelian context of the study, the vegetation indices such as the NDVI are good proxies for detecting variations in humidity and water heights, as they are linked to the chlorophylian activity of the vegetation surrounding the ponds.

Moreover, it is interesting to note that water heights could be monitored with MODIS imagery not only for larger ponds as Barkedji (347,400 m^2), but also for smaller ponds of about 2000 m^2 such as Furdu and Mous, which were not detected as ponds using a single date of MODIS imagery according to the results of the spatial resolution analysis. This suggests a complementary use of optical EOS for water body detection and monitoring in arid areas. Indeed, for the MODIS sensor to be efficient in the monitoring temporal dynamics of smaller ponds, they must be geo-located beforehand. If the monitoring begins just before the beginning of the rainy season, an initial reference state can be obtained from which it would be possible to track successive filling phases of each pond during the rainy season. Even if the water height cannot be directly obtained, the hydrological phasing of the water bodies is in itself an interesting parameter that could be useful to various disciplines.

1. **Conclusion**

In this paper, we reviewed available methods of locating and monitoring temporary water areas, in terms of their spatial and temporal resolutions and spectral indices, over large areas in arid lands. The study highlights three main results that are validated with field data. Until now, among the water indices tested (MNDWI, $NDWI_1$, $NDWI_2$ and NDVI) from a Landsat ETM+ image, the MNDWI and the $NDWI_2$, which both use the MIR band, are found to be more efficient for detecting water bodies in arid areas. However, our study of

the effects of resolution on detection of temporary ponds showed that the resolution could improve a less efficient index like the NDVI or the $NDWI_1$. Herein we have provided detailed criteria to help any user choose the optical sensor best fitted to the minimum size of ponds that need to be located. Finally, the results of the temporal study demonstrated the potential of EOS, like MODIS, to monitor small ponds dynamics; the analysis of MODIS data time series enables the identification of important rainfall events, and thus enables estimation of the filling phases of small ponds, even if they have not been detected in MODIS images.

Results concerning the location and the monitoring of water bodies using EOS should prove interesting for a large array of applications: in epidemiology, for the prevention of vector-borne diseases, and especially to study and assess ponds known to be favorable mosquito breeding sites (Mondet, 2005); in pasture land management, for water resource assessment; and in ecology, to contribute to the preservation of threatened ecosystems that natural habitats to a variety of species.

Acknowledgments

Appendix

The cross-covariance is defined by:

$$\text{cov}[A(t), B(t+\Delta t)] = \frac{1}{n} \frac{\sum_{i=1}^{n}[A(t)-\overline{A}][B(t+\Delta t)-\overline{B}]}{\sigma_A . \sigma_B} \qquad \text{(Equation. 1)}$$

where $A=(a_1,a_2,...,a_{na})$ and $B=(b_1,b_2,...,b_{nb})$ are the two series to be compared (with $na \neq nb$), $\overline{A}$, $\overline{B}$, σ_A and σ_B their respective mean-values and standard deviations and n the number of pairs (a_i, b_j) with a temporal distance $< \Delta t$.

This statistical index allows for the test of whether two temporal series are correlated with a given temporal time-lag. It returns values ranging from -1 (negative correlation) to +1 (positive correlation). A maximum of cross-covariance observed for $\Delta t = \Delta t_{max}$ indicates that the values of the first time series at time t are correlated with the data of the second temporal series at time $t + \Delta t_{max}$.

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Tables

Table 1. Characteristics of the satellite data used in the study

Satellite / Sensor	Acquisition date	Bands and indices available*	Pixel width (m)	Number of images
Quickbird	2005 - 08 - 04	B, G, R, NIR	2.47	1
Landsat7 / ETM+	2000 - 09 - 12	B, G, R, NIR, MIR,	30	1
Terra / MODIS**	Rainy season 2001 and 2002, (from July to November)	B, R, NIR, MIR, NDVI, EVI	231	24
	2005-08-10	B, R, NIR, MIR, NDVI, EVI	231	1

* B: Blue; G: Green; R: Red; NIR: Near Infrared; MIR: Middle Wave Infrared; NDVI: Normalized Difference

Vegetation Index; EVI: Enhanced Vegetation Index

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** Product 'MOD13Q1 MODIS Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V005' (Land

Processes Distributed Active Archive Center, http://lpdaac.usgs.gov/datapool/datapool.asp)

Table 2. Spectral indices from the scientific literature used for water body detection

Index	Band ratios*	Reference
NDVI = Normalized Difference Vegetation Index	(NIR – R) / (NIR+R)	Tucker (1979) ; Towshend and Justice (1986)
NDWI$_1$ = Normalized Difference Water Index	(NIR-MIR) / (NIR+MIR)	Gao (1996),Hardisky (1983);
NDWI$_2$ = Normalized Difference Water Index	(G-NIR) / (G+NIR)	Mc Feeters (1996)
MNDWI = Modified Difference Water Index	(G-MIR) / (G+MIR)	Xu (2006)
NHI = Normalized Humidity Index NDPI = Normalized Difference Pond Index	(MIR-G) / (G+MIR)	Clandillon, (1995), Lacaux & al (2007)

* NIR: Near Infrared; R: Red; G: Green; MIR: Middle Infrared

Figures

Figure 1:

Part of the study area (~11*10 km), centered on the Barkedji village, Ferlo Region, Senegal. The yellow line indicates the contours of Barkedji, Mous, Furdu ponds.

Figure 2

Results of the ROC (Receiver Operating Characteristic) analysis of four spectral indices used for water body detection in a Sahelian area.

Figure 3

Values of MNDWI, NDVI, NDWI$_1$ and NDWI$_2$ indices derived from a Landsat ETM+

image for different land cover types, Ferlo region, Senegal.

Figure 4

Relationship between spatial resolution of remote sensing images and the characteristics of detected ponds (area and number).

The line corresponds to the simulated values (degradation of the Quickbird image spatial resolution). The dots indicate the spatial resolution of the main optical EOS (QuickBird, Ikonos, SPOT 4, SPOT 5, Landsat, Modis, SPOT Vegetation).

Figure 5

Cross-covariance of (a) water-levels and MODIS NDVI data, (b) water-levels and MODIS NDVI from July to September and (c) rainfall and water-levels. The Mous, Furdu, and Barkedji ponds, in the Ferlo region, Senegal, 2001-2002.

The red line indicates the temporal-lag with the maximum value for the cross-variance index. Dot-lines are envelopes of the 95% confidence interval of the cross-covariance, under the assumption of randomness.