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# Normalized difference water indexes have dissimilar performances in detecting seasonal and permanent water in the Sahara–Sahel transition zone

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SUMMARY

The decrease of water resources can enhance poverty and increase insecurity in dry regions, at the same time leading to loss of biological diversity. For these reasons, the information about surface perennial and well-known water sources in the arid and semi-arid regions of Africa has been mapped. However, seasonal water can be missed in mapping due to their short and erratic appearance, while the mapping of any aquatic resources represents a foremost priority for protecting social, economic and biological values in the e.g. Sahara–Sahel transition zone. Therefore, Remote Sensing becomes crucial to monitor a variety of wetland systems in these regions. This work evaluates the performance of three Normalized Difference Water Indexes [Gao's NDWI ($NDWI_{NIR/MIR}$), McFeeters' NDWI ($NDWI_{G/NIR}$) and Xu's NDWI ($NDWI_{G/MIR}$)] in mapping of water systems across Mauritania. Maps with seasonal and permanent water were derived, using a multi-temporal series of Landsat 5 TM and Landsat 7 $ETM^+$ images. The performance of indexes was compared based on 551 control points collected during five fieldwork missions to Mauritania between 2007 and 2011. Control points were separated in three classes of water availability (permanent, seasonal and non-water points) and then randomly assigned into two data sets: one for selecting the water availability thresholds for index reclassification and another for threshold validation. $NDWI_{G/MIR}$ and $NDWI_{NIR/MIR}$ had good performances in detecting permanent and seasonal water, respectively, while $NDWI_{G/NIR}$ failed to detect most of the water bodies. The threshold selection generated water maps with seasonal and permanent features that might be missing in simple mapping of aquatic systems. The extensive data collection provides novel information about NDWI performances for water delineation in arid and semi-arid regions and for a future management of aquatic environments of the Sahara–Sahel transition zone.



## 1. Introduction

In the arid and semi-arid regions of Africa, information about surface water availability has been mostly based on maps of perennial water bodies, maximum extents of wetlands, well-known rivers, and potential drainage networks (Haas et al., 2009). Determining the spatial location of aquatic habitats and associated hydrological connections in arid regions is difficult, since they are generally small, numerous, temporal and spread over large and often remote areas (Ward, 2009). Different types of water bodies may also present distinct levels of vegetation cover and turbidity degrees (Lacaux et al., 2007). Because of the high inter and intra-annual water variability that characterize these regions, seasonal waters can be missed in mapping due to their short and erratic appearance (Haas et al., 2009).

The development of methodological approaches improving the quality of water mapping are mostly important for arid and semi-arid regions, where water scarcity urges detailed information and consistent monitoring (Lehner and Döll, 2004; Shine and Mesev, 2007; Schuol et al., 2008). Assessment of aquatic resources represents a major priority for protecting social, economic and biological values along the Sahara–Sahel transition zone (Shine and Mesev, 2007; Lebel and Ali, 2009; Bader and Latif, 2011). The degradation of such scarce resources represents a key factor enhancing poverty, insecurity and biodiversity loss (McNeely, 2003). The constant demand for natural resources has caused several social tensions and increased violent conflicts in the Sahara–Sahel transition zone (McNeely, 2003; Schuol et al., 2008; Abdalla, 2009), and the recent climate change has forced local farmers to adjust constantly to new conditions (Hein and de Ridder, 2006; Frappart et al., 2009; Hein et al., 2011; Leblanc et al., 2011).

Within the Sahara–Sahel transition zone, southern Mauritania illustrates the need for the quantification of water availability.

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There are two major types of aquatic habitats in Mauritania: water pools in rocky outcrops and temporary floodplains, locally known as *gueltas* (Fig. S1, A, C and E) and *tâmoûrts* (Fig. S1, B, D and F), respectively. *Gueltas* are located upstream of narrow valleys at the base of mountains and they are usually small (varying between 0.001 ha and 1.0 ha), deep, and supplied by torrential waterfalls during the rainy season, between July and October (Cooper et al., 2006; Brito et al., 2011). *Tâmoûrts* are located on the foothills of mountains, and are normally large (more than 1000 ha) and shallow, being frequently covered by hydrophytes and surrounded by Acacia trees (Cooper et al., 2006; Shine and Mesev, 2007). *Tâmoûrts* are mostly arid during the dry season, because of the low deepness and frequent exploitation for watering domesticated animals (Cooper et al., 2006). Both *gueltas* and *tâmoûrts* are generally isolated and spatially restricted, being highly vulnerable to human activities and climate change (Shine and Mesev, 2007; Trape, 2009).

An accurate estimation of water availability is needed for conserving the Sahara–Sahel biological values. The major mountains of Mauritania, Adrar Atar, Tagant, Assaba and Afollé (Fig. 1), hold isolated populations of several vertebrate species of Afro-tropical origin (Trape, 2009; Brito et al., 2010, 2011). During the rainy season, raging water fills streams, partially connecting many *gueltas*, and flows to the lower Senegal river, through the Gorgol el Abiod, Gorgol el Akhdar and Garfa basins (Fig. 1). As the persistence of several Mauritanian relict populations depends on mountain humid habitats and associated hydrological corridors, it is very important to evaluate the structure and availability of those habitats.

Remote Sensing (RS) has proven to be a useful solution for monitoring a variety of wetland systems in regions where field investigations are difficult to perform (Ahmed et al., 2009). These techniques have been explored in the arid and semi-arid regions of North Africa for producing maps with the exact location of water bodies and with detailed information about pond dynamics, vegetation cover, and turbidity (Chipman and Lillesand, 2006; Lacaux et al., 2007; Shine and Mesev, 2007; Niang et al., 2008; Leblanc et al., 2011).

Specific RS methods were developed for water assessment, such as the Normalized Difference Water Indexes, NDWIs (Gao, 1996; McFeeters, 1996; Zarco-Tejada et al., 2003; Jackson et al., 2004; Chipman and Lillesand, 2006; Ouma and Tateishi, 2006; Xu, 2006; Lacaux et al., 2007; Zhang et al., 2008; Soti et al., 2009; Ji et al., 2009). The NDWI is a ratio combining two different bands that enhances water spectral signals by contrasting the reflectance between different wavelengths and removing a large portion of noise components in different wavelength regions (Ji et al., 2009). The near-infrared (NIR) band has been referenced as well-suited for detecting open aquatic surfaces from satellite images, since water has a stronger absorptive capacity in the NIR range (McFeeters, 1996; Verdin, 1996). The middle infra-red (MIR) band is also efficient, because water has very high MIR absorption and other landscape components have higher reflectance of MIR than NIR (Gao, 1996; Xu, 2006). Several NDWIs combining the NIR and/or MIR bands have been proposed. The most frequently used NDWIs are: (1) the $NDWI_{NIR/MIR} = (NIR - MIR)/(NIR + MIR)$ (Gao, 1996); (2) the $NDWI_{G/NIR} = (green - NIR)/(green + NIR)$ (McFeeters, 1996); and (3) the modified NDWI, $NDWI_{G/MIR} = (green - MIR)/(green + MIR)$ (Xu, 2006). These indexes range between $-1$ and $+1$, which forces the definition of specific thresholds of NDWI reclassification to separate water from other land cover components. However, threshold definition is uncertain due to the intrinsic water characteristics and land cover complexity of distinct regions (Xu, 2006; Ji et al., 2009). Therefore, threshold definition is specific to each study case. Several studies have developed

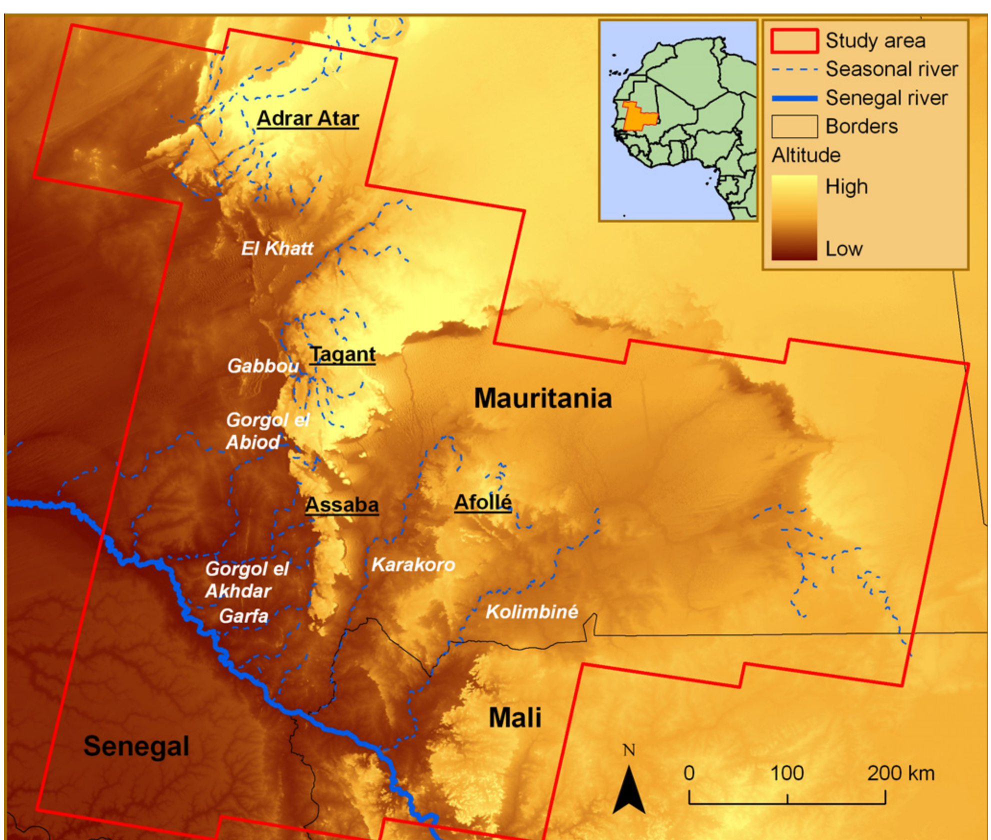


**Fig. 1.** Study area where Remote Sensing techniques were used for the detection of water availability, discriminating main mountain massifs (underlined) and major hydrographical networks (italics) in Mauritania.

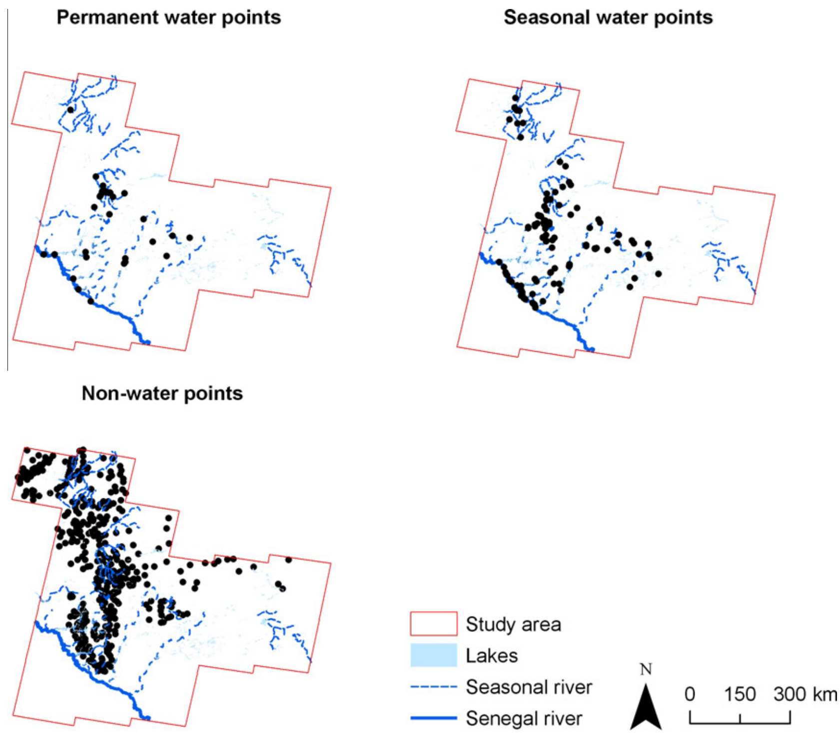


**Fig. 2.** Distribution of permanent water, seasonal water, and non-water control points collected during five fieldwork campaigns to Mauritania.

different thresholding methods, such as the logical standard threshold (water ⩾ 0) (Gao, 1996; McFeeters, 1996; Xu, 2006); arbitrary thresholds determined by photo-interpretation (Lacaux et al., 2007); or thresholds derived from experimental trials (Chipman and Lillesand, 2006; Ji et al., 2009). Despite the considerable number of studies addressing water delineation, there have been divergent opinions concerning which index should be chosen and how thresholds should be established (Ouma and Tateishi, 2006; Lacaux et al., 2007; Zhang et al., 2008; Soti et al., 2009; Ji et al., 2009).

In this study, water resources are evaluated across the arid and semi-arid regions of Mauritania with remote sensing techniques in order to: (i) assess the performance of $NDWI_{NIR/MIR}$, $NDWI_{G/NIR}$ and $NDWI_{G/MIR}$ for mapping seasonal and permanent water; (ii) develop a methodology of threshold selection that assures the best classification of variable water-availability systems; and (iii) create water availability maps for central-southern Mauritania.

## 2. Methods

### 2.1. Study area

The study area encompasses nearly 463,925 km$^2$, between 21°N and 13°N and 14–5°W, and comprises the central and southern Mauritania (76% of study area), extreme south-western Mali (13%) and north-eastern Senegal (11%) (Fig. 1). Within Mauritania, the study area includes the major mountains of Adrar Atar, Tagant, Assaba and Afollé. While the Adrar Atar is relatively isolated, the other three massifs can be connected by seasonal rivers that occasionally flow to the Senegal river. Altitude varies from 9 m on the Senegal river valley to 793 m in the Adrar Atar. Climate is characterized by a cool and dry period from November to February and a hot, dry period from March to June (Cooper et al., 2006). The annual average temperature is moderately homogeneous, varying between 26.6 °C in the Tagant and 30.8 °C in the lowland Aouakâr sand sea (Hijmans et al., 2005). Annual precipitation has a north–south gradient, ranging from 98 mm in the northern desert areas up to 884 mm in the southern savanna regions (Hijmans et al., 2005). Annual rains are scarce and seasonal, falling in a single wet season from July to October, with most precipitation in August and September (Cooper et al., 2006; Ahmed et al., 2008). Highlands are covered by sparse and poorly diversified desert steppe vegetation (Tellería et al., 2008). Lowlands are covered by trees (usually *Acacia nilotica*) and marshlands that are used by sedentary farmers for cultivation (Tellería et al., 2008). The land cover is composed in the north by stony and sandy desert with dunes and in the south by croplands and shrubs, interspersed between annual and perennial grasses (Fensholt et al., 2009).

### 2.2. Field data

A total of 551 control points were collected during five fieldwork missions to Mauritania between 2007 and 2011, and separated in three classes according to water availability: (1) permanent water points, where water is yearly present ($N = 34$); (2) seasonal water points, where water is present at least in 1 month of the year ($N = 118$); and (3) non-water points, where water is never available throughout the year, like rocky areas or dunes ($N = 399$) (Fig. 2). The classification of each site as permanent or seasonal was based on inquiries to local people and visual evaluation of likelihood of water availability. The difference between sample sizes of the three classes reflects the water availability present in the study area: few locations with permanent water available and vast areas where water is not available. The coordinates of the control points were gathered from a Global Positioning System (GPS) receptor, Trimble Nomad, on the datum WGS 1984 UTM (Zone 29 N).

### 2.3. Remote sensing data

Satellite images from the Landsat 5 Thematic Mapper (TM) series were obtained through the Global Visualization Viewer (GLOVIS; http://glovis.usgs.gov/) of the United States Geological

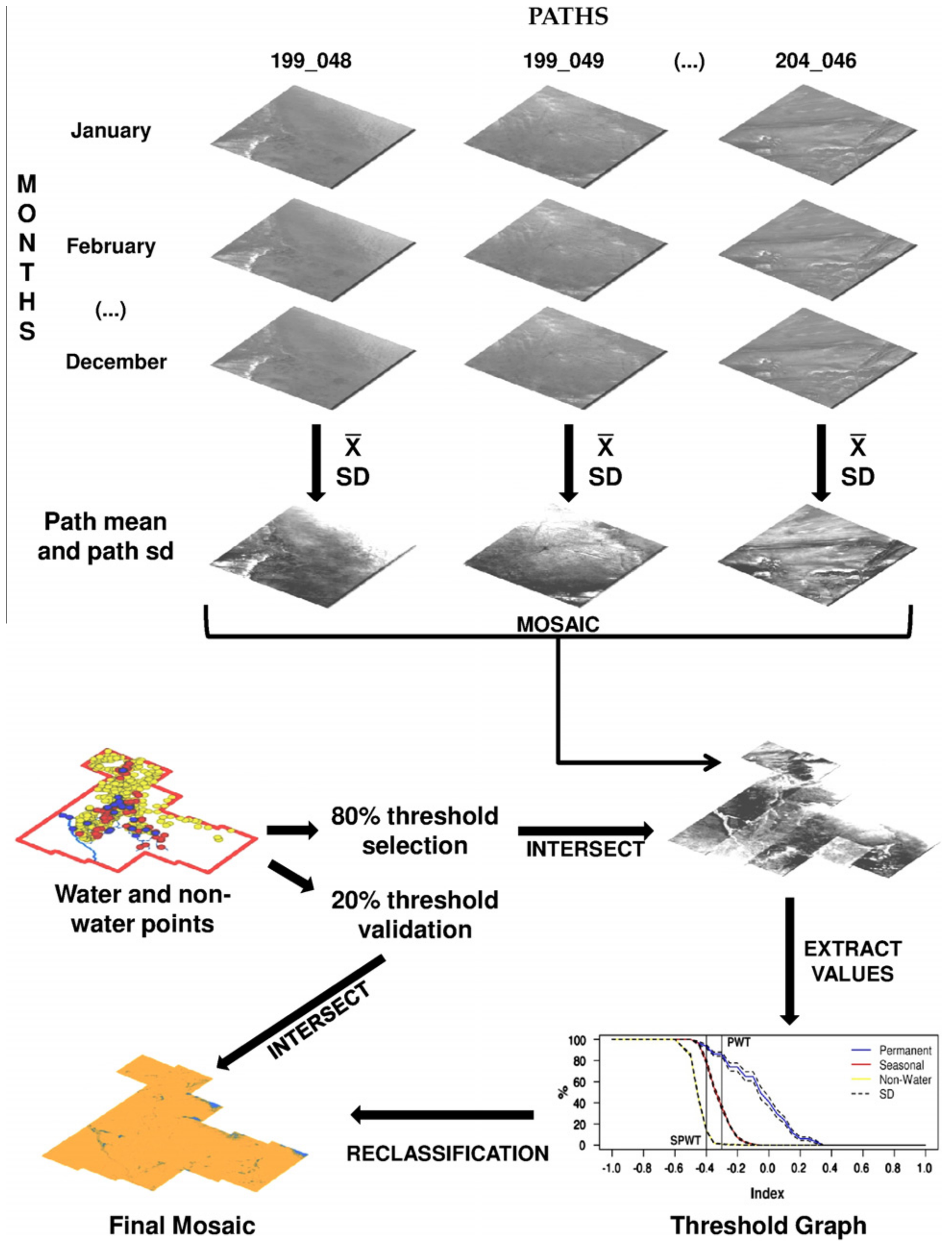


**Fig. 3.** Overview of the methodology to derive the final mosaic of water availability. The procedure was performed for each of the three indexes tested. Each group of control points were split randomly into two data sets: 80% for threshold selection and 20% for threshold validation. This process was repeated independently 10 times. The reclassification was based on the water thresholds (WTs) and permanent water thresholds (PWT) defined the mean index values of the control points.

Survey (USGS) (Table S1). One image per month, between 2001 and 2010, for each of the 17 Landsat scenes of our study area was analyzed (*Fig.* S2). Whenever cloud cover was higher than 10%, the time series was completed with images from the Landsat 7 ETM$^+$, also available at GLOVIS (Table S1). The final dataset comprised 204 satellite images, with a spatial resolution of 30 m (Tables S1 and S2). The Landsat images were georeferenced and atmospheric corrected by the USGS (http://landsat.usgs.gov/). All analyses were developed in the ArcGIS 9.3 software (ESRI, 2008) on the datum WGS 1984 UTM (Zone 29 N).

### 2.4. NDWI calculation

$NDWI_{G/MIR}$, $NDWI_{NIR/MIR}$ and $NDWI_{G/NIR}$ were calculated for each image using the *Spatial Analyst* extension for ArcGIS. After calculations, 6 km edges were removed from each image in order to avoid lateral data discontinuities. Mean and standard deviation (SD) of the 12 monthly images for each Landsat scene were calculated for each index (Fig. 3). The resulting images were used to build mosaics

**Table 1**
Optimized thresholds for the classification of NDWI indexes as water (WT) and permanent water (PWT), and mean ± standard deviation of correct classification rates of threshold-selection control points (non-water, seasonal and permanent water) according to each threshold.

| | Index | Threshold | Non-water | Seasonal | Permanent |
|---|---|---|---|---|---|
| WT | $NDWI_{G/MIR}$ | −0.4 | 14.3 ± 0.58 | 79.8 ± 2.55 | 93.6 ± 1.56 |
| | $NDWI_{NIR/MIR}$ | −0.2 | 6.3 ± 0.61 | 82.8 ± 1.86 | 94.6 ± 2.62 |
| | $NDWI_{G/NIR}$ | −0.1 | 3.8 ± 0.42 | 8.0 ± 1.15 | 59.3 ± 3.90 |
| PWT | $NDWI_{G/MIR}$ | −0.3 | 0.9 ± 0.29 | 36.2 ± 2.39 | 86.2 ± 1.79 |
| | $NDWI_{NIR/MIR}$ | −0.1 | 0.0 ± 0.0 | 17.4 ± 1.44 | 73.6 ± 4.8 |
| | $NDWI_{G/NIR}$ | −0.05 | 0.0 ± 0.16 | 1.8 ± 0.45 | 51.5 ± 4.08 |

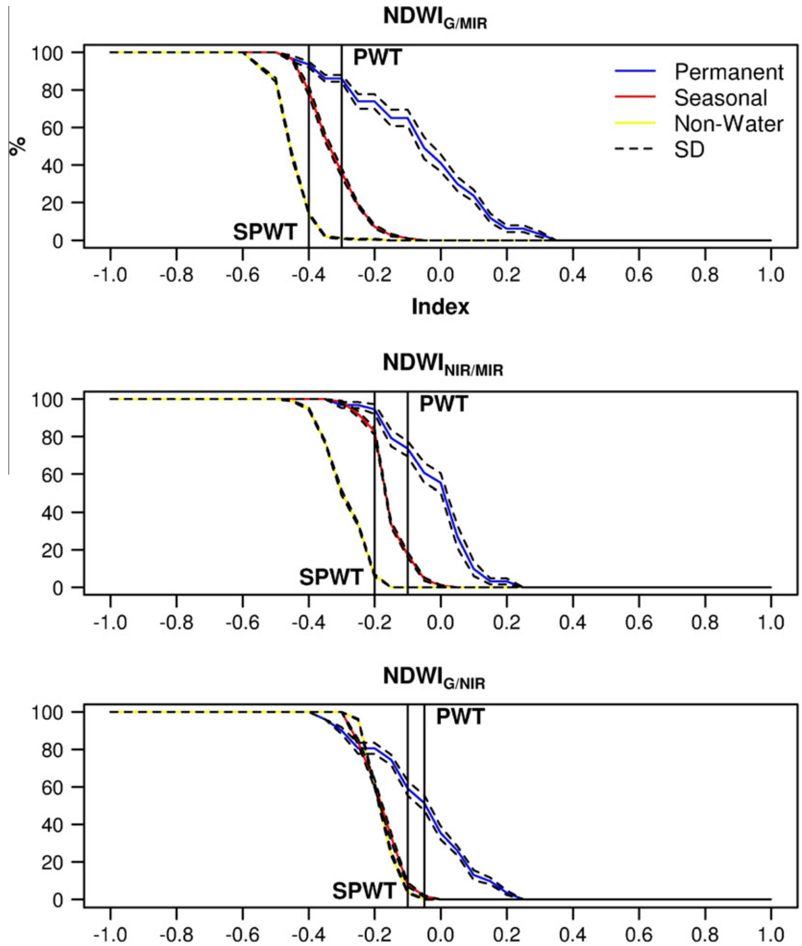


**Fig. 4.** Mean (solid lines) and standard deviation (dotted lines) of classification rates of 10 random data sets of three classes of control points (permanent, seasonal and non-water) along increasing thresholds for identifying water availability applied to mean $NDWI_{G/MIR}$, $NDWI_{NIR/MIR}$ and $NDWI_{G/NIR}$. The water threshold (WT) and permanent water threshold (PWT) for the three indexes are indicated (vertical lines).

**Table 2**
Mean ± standard deviation of correct classification rates of threshold-validation control points as permanent, seasonal and non-water according to classified NDWI indexes.

| Index | Non-water | Seasonal | Permanent |
|---|---|---|---|
| $NDWI_{G/MIR}$ | 97.6 ± 1.71 | 49.4 ± 9.92 | 95.8 ± 6.76 |
| $NDWI_{NIR/MIR}$ | 94.9 ± 2.38 | 77.6 ± 8.15 | 72.7 ± 15.8 |
| $NDWI_{G/NIR}$ | 95.9 ± 1.85 | 6.20 ± 4.64 | 58.5 ± 15.6 |

**Table 3**
Number of permanent and seasonal water pixels detected by the three NDWI indexes. The total number of water pixels represents the sum between the permanent and seasonal pixels.

| Index | Permanent water | Seasonal water | Total |
|---|---|---|---|
| $NDWI_{G/MIR}$ | 3,135,196 | 9,677,056 | 12,812,252 |
| $NDWI_{NIR/MIR}$ | 1,264,041 | 32,965,003 | 34,229,044 |
| $NDWI_{G/NIR}$ | 876,741 | 3,333,377 | 4,210,118 |

with mean and SD for the three indexes. Maximum values were chosen for overlapping areas during the construction of mosaics.

### *2.5. Threshold selection, NDWI performances and water maps*

The control points were used to identify optimized thresholds for NDWI reclassification and to evaluate NDWI performances in distinguishing water/non-water and permanent/seasonal locations. Firstly, control points were randomly assigned, using Hawths Tools 3.27 (Beyer, 2004) extension for ArcGIS, into two data sets: 80% for threshold selection (corresponding to 27, 94 and 319 points of permanent, seasonal and non-water locations, respectively) and 20% for threshold validation (corresponding to 7, 24 and 80 points of permanent, seasonal and non-water locations, respectively). The process of random selection was repeated to generate 20 independent data sets (10 data sets for threshold-selection points, and 10 data sets for threshold-validation points). Secondly, each data set of threshold-selection points were intersected with mean mosaics, using Hawths Tools (Fig. 3). Plots were derived depicting the average relative number of each of the three classes of threshold-selection points. Thirdly, profiles of average curves were used to identify two thresholds: (1) water threshold (WT), which discriminated pixels with water from those with no water; and (2) permanent water threshold (PWT), which distinguished pixels with permanent water from pixels with seasonal water or no water. The WT corresponds to the mean NDWI value that maximizes the average number of water points and minimizes the average number of non-water points on those pixels defined as water by the WT. The PWT corresponds to the value that maximizes the number of permanent water points and minimizes the number of seasonal water points on those pixels defined as permanent water by the PWT. Fourthly, mean mosaics were reclassified according to the identified WT and PWT thresholds into three classes of water availability: non-water, seasonal water and permanent water (Fig. 3). Finally, each data set of threshold-validation points was intersected with reclassified water-maps (Fig. 3) to calculate average percentages and standard deviations of correct classification of each of the three classes of control points by the reclassified water maps.

The control points were also intersected with the SD mosaics to assess the index deviation for permanent, seasonal and non-water locations.

## 3. Results

### 3.1. Threshold selection and NDWI performances

The water (WT) and permanent water (PWT) thresholds varied between −0.05 and −0.40 (Table 1, Fig. 4). The identified thresholds were coherent amongst the 10 data sets of threshold-selection control points, and the low standard deviation (SD) and similarity of profiles of curves confirmed the consistency of results (Fig. 4). All index values were low in non-water areas and in the three data sets: 100% of non-water points had negative values. When the NDWIs reached a certain mean value, the profile for non-water points decreased abruptly, followed by the decrease of water points, except for the $NDWI_{G/NIR}$, for which non-water points collapsed in a similar way as the seasonal water points. Most of the seasonal points had small index values for the three NDWIs: for the $NDWI_{NIR/MIR}$ and $NDWI_{G/NIR}$, 96% and 98% of the seasonal points had values lower than −0.05, respectively, while for the $NDWI_{G/MIR}$, 97% of these points had values under −0.15. Except for $NDWI_{G/NIR}$, the profile for seasonal points started to decrease when the percentage of non-water points was below 50% (−0.45 for $NDWI_{G/MIR}$

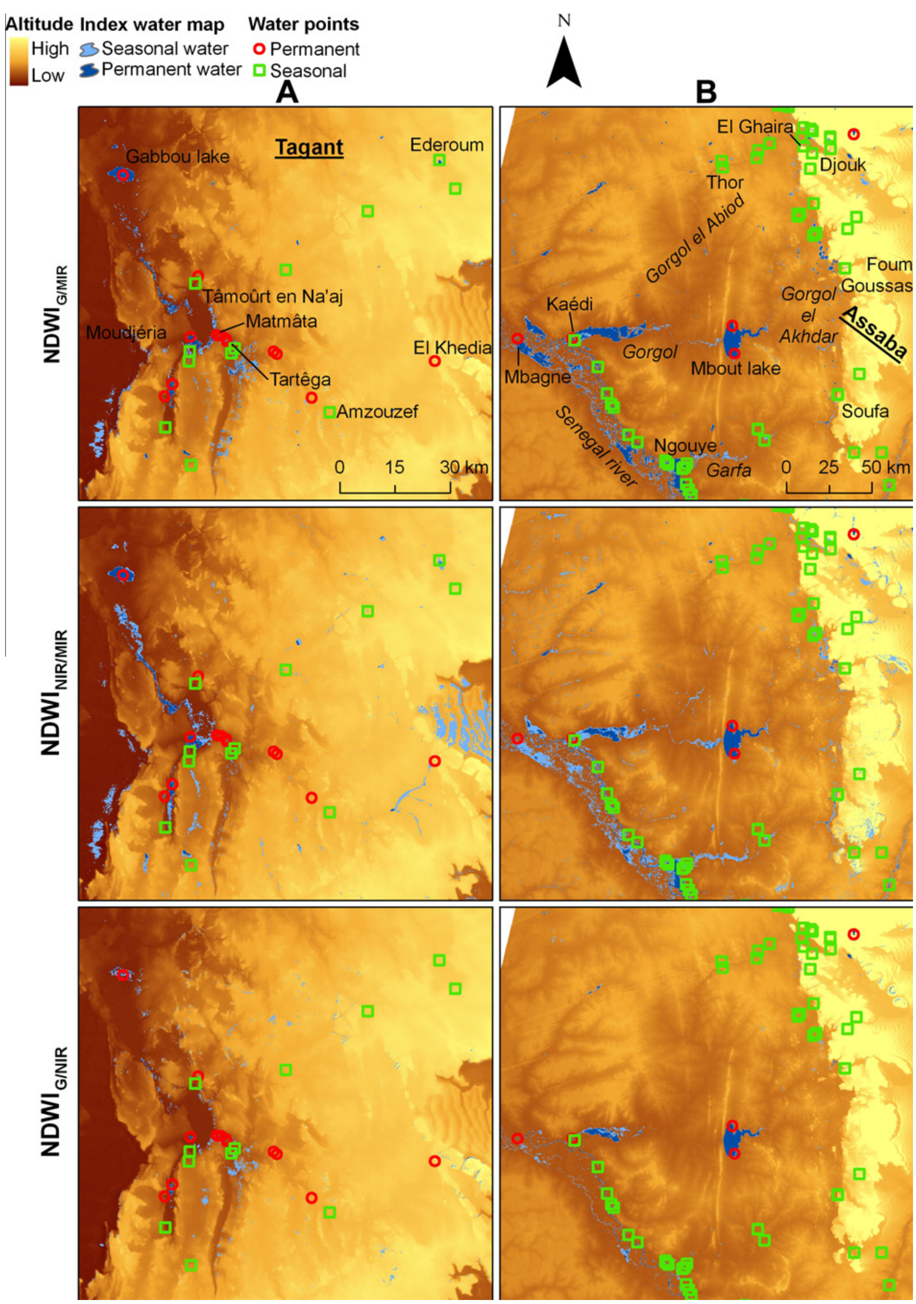


**Fig. 5.** $NDWI_{G/MIR}$, $NDWI_{NIR/MIR}$ and $NDWI_{G/NIR}$ reclassified water maps for two regions with relevant hydrographic networks: (A) Gabbou basin and (B) Senegal river, Gorgol el Abiod, Gorgol el Akhdar and Garfa basins. Pixels with permanent and seasonal water are in dark and light blue, respectively. Red dots and green squares represent permanent and seasonal water points, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and −0.25 for $NDWI_{NIR/MIR}$). The permanent points had the highest index values: at least 70% of permanent points had values greater than −0.20 in all indexes. The profile for permanent points decreased smoothly, in comparison to the non-water and seasonal points, and descent peaks were found at higher index values: −0.20 in $NDWI_{NIR/MIR}$ and $NDWI_{G/NIR}$ and −0.10 in $NDWI_{G/MIR}$.

According to the 10 data sets of threshold-validation points, at least 95% of non-water points were correctly classified by all indexes (Table 2). The highest correct classification rates and relatively low standard deviation of permanent and seasonal points were obtained with the $NDWI_{G/MIR}$ and $NDWI_{NIR/MIR}$, respectively, while the $NDWI_{G/NIR}$ had the lowest rates of correct classification of water points, in both threshold-selection and -validation points (Tables 1 and 2).

The profiles of curves depicting the percentage of control points with increasing NDWI standard deviations were concordant for all indexes (*Fig.* S3). In all cases, the non-water control points had small deviations, while permanent points exhibited higher deviations. The seasonal points had intermediate deviations, and the profiles of the curves were similar between seasonal and permanent points in the $NDWI_{G/MIR}$ and $NDWI_{NIR/MIR}$ and between seasonal and non-water points in the $NDWI_{G/NIR}$.

### 3.2. Water maps

The $NDWI_{NIR/MIR}$ was the index that detected more pixels with water followed by the $NDWI_{G/MIR}$ and by $NDWI_{G/NIR}$, and the $NDWI_{G/MIR}$ was the index that detected more pixels with permanent water (Table 3). All NDWIs detected the Senegal river and other large water features, such as the M'bout lake, and detected minimal water availability between the Assaba and Afollé mountains (Figs. 5, S4–S6). The $NDWI_{G/MIR}$ detected seasonal water in the northern region, north of the Tagant and Adrar Atar, pixels with permanent water along the eastern region, and practically no water south of Senegal river (Fig. S4). The $NDWI_{NIR/MIR}$ distinguished a great part of the northern study area as seasonal water, including southern Adrar Atar and extreme southern portions of the study area, and detected permanent and seasonal water in eastern Mauritania (Fig. S5). In comparison to the other two indexes, the $NDWI_{G/NIR}$ detected fewer water pixels and only identified permanent water in flat areas of north-eastern Tagant and Senegal river, while north-western Adrar Atar and some scattered regions in the eastern part of the study area were identified as seasonal (Fig. S6).

In particular, the NDWIs performed differently in areas considered as hydrologically important (Figs. 5, S4–S6). $NDWI_{G/MIR}$ and $NDWI_{NIR/MIR}$ classified correctly the permanent Gabbou lake and other relevant *gueltas* of the Gabbou basin (Fig. 5A). However, the $NDWI_{NIR/MIR}$ provided the most complete water map for this basin, identifying accurately the water streams flowing to the Gabbou lake. The $NDWI_{G/NIR}$ offered an incomplete water map for this area, classifying the large-sized Gabbou lake (2500 ha) as seasonal. In the Djouk valley, the $NDWI_{G/MIR}$ detected more permanent water bodies while the $NDWI_{NIR/MIR}$ identified the large and seasonal *tâmoûrts* located at the foothills of Tagant and Assaba (Figs. S4 and S5B). The $NDWI_{G/NIR}$ had the worst results, detecting few permanent pixels in the valley (Fig. S6B). The $NDWI_{G/MIR}$ detected the Senegal and lower Gorgol rivers and the M'bout lake as permanent, but failed to detect other important water courses connecting with the Senegal river, such as the Gorgol el Akhdar, Gorgol el Abiod and Garfa rivers (Fig. 5B). The $NDWI_{NIR/MIR}$ identified these water courses in detail, especially the Garfa and the connection among M'bout lake and the lower Gorgol. The index also classified M'bout, the Senegal river, and most of the lower Gorgol river as permanent water. The $NDWI_{G/NIR}$ classified correctly the M'bout lake and the lower Gorgol and Senegal rivers as permanent, but did not detect any water connecting these major hydrological courses. Similar patterns among indexes were observed in the Karakoro basin (Figs. S4, S5 and S6D–E). The $NDWI_{NIR/MIR}$ detected more water in this area, especially seasonal water in the lower Karakoro. The $NDWI_{G/MIR}$ detected water in the upper and lower Karakoro, but despite identifying more sites with permanent water, it detected less hydrological connections than the $NDWI_{NIR/MIR}$ in this basin. The $NDWI_{G/NIR}$ detected very few water pixels, failing in the classification of the entire Karakoro, despite classifying correctly the permanent lakes of Boubleïne and Kankossa.

## 4. Discussion

### 4.1. Sources of uncertainty

The restricted temporal resolution of Landsat satellites limited the selection of a complete time-series for the present work, which probably affected the accuracy of water variability (Jackson et al., 2004; Zhang et al., 2008). The satellite imagery covered areas outside Mauritania, like north-eastern Senegal and south-western Mali, where control points were not available. Security reasons (Abdalla, 2009; Walther and Retaillé, 2010) also hampered the data collection in eastern Mauritania. Therefore, caution is required while interpreting water availability estimations in these regions.

Despite the relevant contribution of Landsat satellites for extracting data from remote regions, the use of satellite imagery with higher temporal resolution (e.g. MODIS satellite) could be helpful to improve the delineation quality of variable water systems. However, high temporal resolution satellites have usually low spatial resolution, which could prevent the development of detailed water maps for hydrological significant areas.

### 4.2. Threshold selection and NDWI performances

The low values attributed to most of non-water points demonstrated that the three NDWIs are sensible to separate water features from dry areas. The control points assigned negative index values for almost all seasonal points, an unexpected result given the theoretical value for water features: water $\geqslant 0$ (McFeeters, 1996). The soils of these regions are composed by large proportions of silt, inducing water streams to become muddy and loaded with suspended sediments. Moreover, human activities in these dry regions, water-extraction for agriculture, domestic and cattle needs (Cooper et al., 2006), may also amplify water turbidity (Fig. S1). Therefore, ponds may present similar traits to bared soils, which could lead to underestimations (Lacaux et al., 2007). The short time availability of seasonal waters in Mauritania could be an additional explanation for this fact. Since annual rains are scarce, the few months with available water may not be representative for inducing a positive average in the final mosaics. As expected, most of the permanent water points had positive NDWIs, indicating that these methods can detect complex hydrological streams and secondary permanent waters.

The standard deviation of the control points indicates the coherency of the three water indexes. Non-water points had lower deviations, reflecting the continuous scarcity of water in these locations. Seasonal sites, despite having higher deviations than non-water locations, presented low index variability; probably because these places are dry throughout most the year, having limited spectral variances. Permanent water points showed high index variability that may be related to annual variations of water levels, which affects water turbidity and reflectance (Lacaux et al., 2007; Soti et al., 2009). The great income of sediments brought by seasonal floods may also affect index variability.

The control points allowed setting and validating optimized thresholds, and thus, evaluating the performance of NDWIs in distinguishing water/non-water and seasonal/permanent water. Ground-validation has been referenced as a helpful method for monitoring water bodies in arid areas, allowing direct comparisons between different indexes for identical situations and quantitative assessments of relative NDWI performances (Soti et al., 2009). In the present study, $NDWI_{G/NIR}$ exhibited serious limitations in detecting water features, corroborating its inadequacy for precise water delineation (Ouma and Tateishi, 2006; Xu, 2006; Soti et al., 2009). The $NDWI_{G/MIR}$ and $NDWI_{NIR/MIR}$ had better performances in separating water from non-water points, confirming the better accuracy of indexes that incorporate the MIR band (Ouma and Tateishi, 2006; Ji et al., 2009; Soti et al., 2009). Similar results were obtained by Soti et al. (2009) for the Sahelian region of northern Senegal. Authors concluded that indexes that combine the NIR and visible bands ($NDWI_{G/NIR}$) are less efficient than indexes that use the MIR band for detecting water bodies in arid areas. However, the present study reveals novel and interesting results. In fact, it was discovered that, for the Sahara–Sahel transition zone, different indexes that use the MIR band had dissimilar performances in detecting seasonal and permanent water. $NDWI_{G/MIR}$ accomplished a better classification of permanent water while $NDWI_{NIR/MIR}$ detected seasonal water with more accuracy. The characteristics of permanent waters may explain the better performance of $NDWI_{G/MIR}$. These water features, usually corresponding to *gueltas*, are generally deep and have small amounts of sediments and vegetation, thus their reflective properties are closer to the typical spectral reflectance of clear water (Lillesand et al., 2008). Permanent waters may have higher MIR absorptions and higher green reflectance, being detected more precisely by $NDWI_{G/MIR}$, while seasonal waters, usually corresponding to *tâmoûrts*, are shallower and surrounded by large vegetation. Suspended sediments could lead to underestimations of seasonal waters, but the presence of vegetation may increase the performance of $NDWI_{NIR/MIR}$ in detecting these features. Given that vegetation has high reflectance of NIR than in MIR, seasonal waters with associated vegetation will probably be identified by $NDWI_{NIR/MIR}$ more accurately. On the contrary, vegetation has generally higher MIR than green reflectance (Lillesand et al., 2008), which should render $NDWI_{G/MIR}$ as less appropriate for detecting seasonal waters surrounded with vegetation.

Different approaches with good performances in detecting vegetation water content, such as the Normalized Difference Vegetation Index (NDVI), could also be useful for identifying seasonal water. In fact, Shine and Mesev (2007) proved that NDVI can detect seasonal water, particularly *tâmoûrts* in Mauritania, since these are usually associated with complex vegetation structures. However, some seasonal water features and most of the permanent water locations of these regions have no vegetation (e.g. permanent *gueltas* of Fig. S1, A, C and E). As such, NDVI would not be so precise in the detection of these important water features. The combination of different NDWI's could be more effective for maximizing detection of water with different availabilities and different vegetation covers.

### *4.3. Water maps*

$NDWI_{NIR/MIR}$ was the index that detected more pixels with water and it over-predicted water features over large areas of northern study area and in north-eastern Adrar Atar. The same trend was observed with $NDWI_{G/MIR}$ but to a lesser extent. Such biases were probably caused by shadow noises associated to the irregularity of sand dunes. Gao (1996) advised for possible overestimations by NDWIs due to shadow noise, arguing that the $NDWI_{G/MIR}$ performs better at suppressing this misleading component.

In the Sahelian regions of Senegal and Mali, large water areas were overestimated by the $NDWI_{NIR/MIR}$. Given the southwards increase of average rainfall in the region, these areas are covered by more complex structures of natural vegetation and composed by distinct soil types (Foley et al., 2003; Frappart et al., 2009; Timouk et al., 2009). Moist-soaked soils and abundant vegetation may have lead $NDWI_{NIR/MIR}$ to detect these landscapes as water.

NDWIs revealed low water availability in the plains separating the mountains of Tagant–Assaba from Afollé, and the Adrar Atar from the southern mountains. The low availability along the Karakoro basin, that separates the Afollé from the Assaba, might be related to the geomorphological characteristics of the later mountain. The bend plateau of the Assaba declines to the west (Toupet, 1966), forcing most of the running water to drain westward and limiting water availability in the upper Karakoro basin. Only the lower Karakoro was detected accurately by $NDWI_{G/MIR}$ and $NDWI_{NIR/MIR}$, probably due to the greater flow accumulations near the Senegal river. The gap between the Adrar Atar and the southern mountains corresponds to the permanently dry and dune-covered El Khatt river basin.

## 5. Conclusions

The extensive effort during five fieldwork campaigns to Mauritania allowed the collection of a major data set that was paramount for achieving the main objectives of this work. Moreover, this data set provided useful information concerning water spatial distribution in a region where the assessment of aquatic resources represents a major priority.

This study showed that independent threshold estimation methods are essential for optimized classification of NDWIs given that indexes can generate distinct water maps for the same areas. The use of optimized thresholds for the Sahara–Sahel transition zone in Mauritania revealed that indexes that combine the NIR and green bands ($NDWI_{G/NIR}$) are less efficient for detecting water bodies in arid areas, confirming previous results (Soti et al., 2009). On the other hand, indexes that use the MIR band ($NDWI_{NIR/MIR}$ and $NDWI_{G/MIR}$) were most reliable in water detection and in the distinction of water availability. It was also discovered that different indexes that use the MIR band can have dissimilar performances in detecting seasonal and permanent water. $NDWI_{NIR/MIR}$ was more sensible for detecting seasonal water despite significant overestimations, while $NDWI_{G/MIR}$ provided accurate permanent water estimations but less precise predictions of seasonal features.

The present work provided important information about the hydrological characteristics of the Sahara–Sahel transition zone in Mauritania, constituting framework data for future management of important aquatic resources. The obtained results should be tested and further analyzed on different study areas, in order to confirm the distinct performances of NDWI's in detecting different water availabilities. Moreover, the application of these techniques in other Sahara–Sahel areas could be crucial for protecting its social and economic values. The accurate water assessment is also needed for protecting local biodiversity. NDWI's should be used in other mountain systems that hold several isolated species (e.g. Air mountains in Niger and Tibesti mountains in Chad), in order to conserve the Sahara–Sahel biological values.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhydrol.2012.07.042.

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