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Use of Spatial Remote Sensing to Study the Temporal Evolution of the Water Retention of Al Massira Dam in Morocco

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ABSTRACT

In Morocco, irrigated agriculture is still very much linked to the climate and the water retention of dams. With climate change, this country is experiencing recurrent drought, which has led to deficits in water inflow from the rivers to the various dams. The Al Massira dam, the area of study, does not escape this trend. This dam is the only surface water source for the irrigated area of Doukkala. Therefore, special attention must be paid to monitoring this resource at this dam. Thus, the proposed study examined the possibilities offered by spatial remote sensing to improve the current information system. It aims to evaluate this dam's reservoir by exploiting the data generated by using satellite images. The Landsat satellite images were used to assess the area of this dam by adopting an approach combining spectral indices with thresholding. Then, the existing relationship between the area of the dam lake were examined, determined by spatial remote sensing and its water retention measured in situ. The results obtained revealed a strong correlation between the two parameters. Therefore, a study was conducted to find the best model for predicting the dam's impoundment based on its lake. The second-degree polynomial model showed a better performance. Given the results obtained, it is recommended to use geospatial methods in the current and prospective monitoring and steering system of water resources.

Keywords: spatial remote sensing, Al Massira dam reservoir, spectral indices, Landsat satellite images, Doukkala irrigated perimeter.

INTRODUCTION

Morocco's agricultural sector is critical to its economic and social development. Its contribution to PIB ranged from 12% to 14% between 2008 and 2018, with an average of about 13%. This sector employs more than 40% of the population. However, it remains highly dependent on climatic conditions and ground and surface water resources (MAPMDREF, 2019).

Throughout its territory, Morocco receives, a rainfall of 140 billion m^3. The potential of water resources is estimated at 22 billion m^{3,} including 18 billion m^3 of surface water and 4 billion m^3 of groundwater. The allocation per resident is about 700 m^3/resident/year. Since 1966, the state has created hydraulic infrastructure with a storage capacity of more than 17.5 billion m^3. This infrastructure allows the volume regulation of 9.5 billion m^3 of water (Harbouze et al., 2019).

The government's policy on surface water mobilization and storage has allowed for the development of irrigated perimeters in the country's central plains. This has resulted in increased productivity of irrigated land and the development of activities upstream and downstream of the agricultural sector. However, since the 1980s, with climate change, Morocco has experienced a succession of wet and dry periods. Drought has become a structural climatic hazard. This hazard has had negative impacts on the agricultural development in irrigated areas by compromising the achievement of expected objectives and this by a decrease in the regulating effect of dams due to deficits in water supply from rivers (ABHOER, 2012).

However, despite the performance recorded, intensive agriculture in irrigated perimeters remains very much linked to water availability at the dams that supply them with irrigation water. In the Doukkala plain, a large irrigated perimeter has been developed and currently totals about 100.000 ha of irrigated land. However, surface water resources are very limited. Indeed, the waters of Oued Oum Er-Rbia, stored at the Al Massira dam, are the only surface water source for this area (ORMVAD, 2020).

Therefore, the dam's water retention level is a determining factor in maintaining the agricultural activity in this area and is a vital resource for the region's population. As a result of continual monitoring of this resource, application of any rational and efficient use approach, as well as implementation of any alternative, supply can be improved. The latter has since become an absolute necessity and priority in order to maintain the sustainability of irrigated agriculture in the region and meet the challenge of better valuing the investments made.

Regarding monitoring, reliable and permanent information on the spatio-temporal variability of the water resource and its availability are of great use for any strategic planning intervention. A permanent vigilance must be instituted to prospectively make the necessary adjustments. Indeed, the law n° 10–95 on water, aimed at the implementation of water planning based on a prospective and concerted vision which takes into account, on the one hand, the evolution of the water resources and, on the other hand, the real and justified water needs. It recognizes that water resource planning is a continuous and dynamic process (ABHOER, 2012).

Indeed, the traditional methods of monitoring by in situ measurements sometimes have limitations and mobilize much more human and material resources as well as consume more time. However, geomatics and remote sensing techniques are currently in full expansion, all over the world, in the monitoring of the state of natural resources. They can provide reliable and inexpensive information on the current state and in the past on these resources. In this sense, introducing any technology to improve the current system of monitoring water resources at the local, regional and national levels is an initiative of capital importance.

Because of repeating data acquired over time or in real-time, space-based remote sensing can give accurate and inexpensive information on environmental change at local, regional, and global scales (ECS, 2011). This technology has increasingly become the primary source of data for monitoring water resources (Feyisa et al., 2014; Acharya et al., 2018; Bhaga et al., 2021). Indeed, using the data generated by satellite remote sensing technologies is considered a promising approach to detect and monitor surface waters from the local and regional level (Palmer et al., 2015; Zhou et al., 2017; Masocha et al., 2018). Using these data is economically cost-effective, as this technique allows for quick repeatable coverage over large areas. The results are more easily exploited for decision-making (Palmer et al., 2015).

Using the capabilities of spatial remote sensing technology and specifically index methods, Acharya et al. (2018) conducted a performance evaluation study of the most widely used water indices. By using a Landsat 8 scene in Nepal, they tested the applicability of Normalized Difference Water Index (NDWI), the Normalized Difference Vegetation Index (NDVI), Modified NDWI (MNDWI), and Automatic Water Extraction Index (AWEI). As a result, the NDVI and NDWI indices performed better for pure water pixels only, whereas MNDWI and AWEI were unable to reject snow cover and shadows. They enhanced accuracy by combining NDVI, NDWI, and AWEI.

A study evaluating the potential of the Normalized Difference Water Index (NDWI), Surface Water Index (LSWI+5), and Modified Normalized Difference Index (MNDVI), derived from the Landsat-8 OLI and the Sentinel-2 MSI, was conducted in the Western Cape, South Africa, for monitoring seasonal surface water amounts (Bhaga et al., 2021). The results revealed that the two sensors used successfully detected and mapped surface water variations. The normalized water level difference index (NDWI) gave the best results and accuracy; however, the surface water level index 5 (LSWI+5) results overestimated the size and presence of surface water bodies, compared to the other indices, especially during the rainy season. The Landsat 8-derived normalized difference water index (NDWI) fared marginally better than the other indices in detecting and mapping surface water bodies (Bhaga et al., 2021).

Feyisa et al. (2014) introduced a new automatic water extraction index (AWEI) that improves classification accuracy in shadow areas and dark surfaces that other classification methods often fail to classify correctly. At four of the five sites tested, the classification accuracy of AWEI was significantly higher than MNDWI and

ML (Pb value 0.01). Therefore, AWEI can be used to extract water with high precision, especially in mountainous areas where deep shadowing caused by terrain is a significant source of classification errors (Feyisa et al., 2014).

On the other hand, and always with the same aim of evaluating environmental changes using spectral information recorded by satellite sensors, a mapping study of the water bodies of Lake Metztitlan in Mexico was carried out using the satellite data from Landsat 5 TM, Landsat 8 OLI and Sentinel 2A at different temporal scenes. Evaluation of the Modified Normalized Water Difference Index (MNDWI) and Automated Water Extraction Index (AWEI) revealed, based on visual inspection, high performance of the AWEI approximated by Landsat 8 Oli (OLI) and Sentinel-2 (MSI) sensors (Arreola et al., 2019).

In the conducted study, the authors hope to contribute to improving the water resource monitoring system by introducing new techniques to assess its availability in terms of volume at the Al Massira dam, which is part of the Oum Er-Rbia watershed. Thus, the present work aimed to characterize the evolution of the availability of water resources in this dam by exploiting the data measured in situ and using satellite images as a new alternative to assess its retention. The ultimate objective of this work is to contribute to the establishment of a geospatial information system at the scale of the irrigated area of Doukkala and contribute to a permanent monitoring of the current and prospective status of the water resource by using technologies, methods and tools of remote sensing, geomatics and GIS. This system makes it possible to provide managers with a range of information to make decisions and guide the management of the resources during the development of the management strategy and action plans for its implementation.

MATERIALS AND METHODS

Study area

The Al Massira dam is located about 150 km south of the city of Casablanca, between Latitude 32° 28’ 52” N and Longitude 7° 38’ 3” W (Figure 1). It is the second largest dam in Morocco and is part of the Oum Er-Rbia basin, one of the largest basins in the country, which covers an area of 35,000 km² with an elongation of 550 km (ABHOER, 2012).

The main characteristics of the Al Massira dam are presented in the Table 1 (Alaoui et al., 2000). This dam is the only source of surface water for the Doukkala irrigated perimeter, which totals an irrigated area of about 100,000 ha.

Table 1. Main characteristics of the Al Massira dam

Parameters	Values
Year of impoundment	1979
Watershed area (km^2)	28500
Maximum depth (m)	40
Average depth at normal water level (m)	20
Length (km)	30
Maximum width (km)	10
Normal elevation (NGM)	285
Maximum elevation (NGM)	287,5
Water intake elevation (NGM) (*)	240
Volume at normal level (10^6 m^3)	2800
Residence time (months)	10-42

Note: (*) ie + 10 m above the bottom of the reservoir (230 NGM).

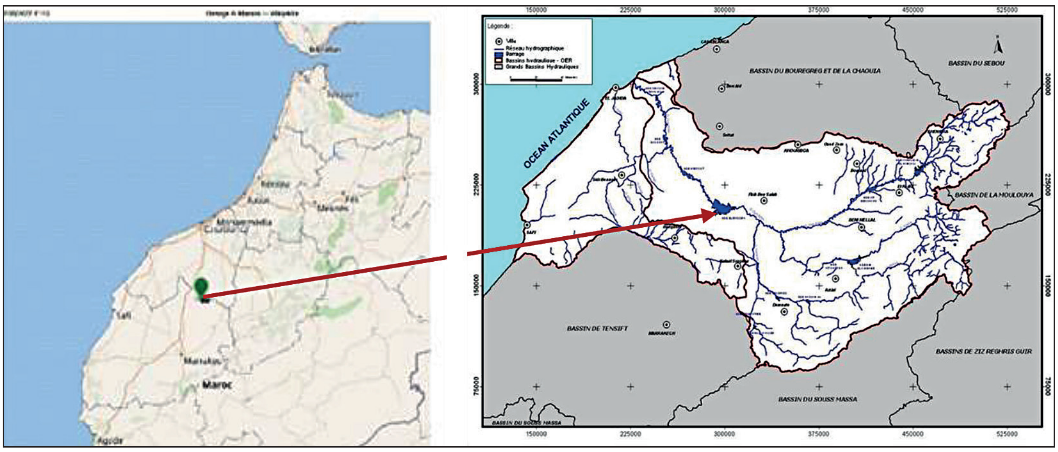

Figure 1. Study area, Al Massira dam, Morocco

Data used

In the framework of this study, the following were used: (i) Data related to the evolution of the Al Massira Dam reservoir available at the Regional Office of Agricultural Development of Doukkala (ORMVAD, 2010–2020) and the Ministry of Equipment and Water (MEE, 2022); (ii) Data generated by Landsat satellite images that cover the Al Massira Dam lake during August and September of each year from 1999 to 2021.

Methodology adopted

Preparation of satellite data

Landsat is a satellite imagery program for collecting high-resolution (30 m) earth images since 1972. It provides a valuable temporal record for identifying spatio-temporal trends in landscape change. Landsat 4-5 TM (Thematic Mapper) and Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) surface reflectances, collection 2 are generated using the LEDAPS (Landsat Ecosystem Disturbance Adaptive Processing System) algorithm (Masek et al., 2006); while Landsat 8 OLI (Operational Land Imager) surface reflectance data, collection 2 are generated using the Land Surface Reflectance Code (LaSRC) (Vermote et al., 2016). They are closely related and relatively easy to consolidate into a coherent time series with a spatial resolution of 30 meters. The preparation of the data was carried out using the Google Earth Engine (GEE) platform by performing operations according to the Figure 2 (Bounif et al., 2021).

The Landsat 4/5 (ETM), Landsat 7 (ETM+) and Landsat 8 (OLI) satellite images from August and September of each year over the period 1999 to 2021 were selected at the Google Earth Engine (GEE) platform. However, Roy et al. (2016) have shown that there are small but potentially significant differences between the spectral characteristics of Landsat ETM+ and OLI. To overcome this limitation, the terrestrial images were harmonized by transforming the surface reflectance of TM and ETM+ to OLI using Ordinary Least Square (OLS) regression coefficients with a slope and intercept constant of each band (Table 2) (Roy et al., 2016).

For cloud and shadow masking, the CF mask algorithm which uses the pixel_qa band to perform this operation was applied (Zhu et al., 2015). The data ready for analysis should have masked clouds and cloud shadows.

Finally, we proceeded to calculate the indices to estimate the surface of the Al Massira dam lake. The selected indices are presented in the Table 3.

McFeeters (1996) developed the normalized difference water index (NDWI) using the green and near-infrared (NIR) bands of a Landsat Thematic Mapper (TM) image to maximize the identification of water features. He proposed zero thresholds to separate water from the background (McFeeters, 1996). Xu noticed that the zero thresholds did not separate water bodies from built-up areas. He replaced the near-infrared (NIR) band of McFeeters' NDWI with the shortwave infrared (SWIR) band and derived the modified NDWI (MNDWI) to solve this problem (Xu, H, 2006). However, significant issues remain due to shadows in mountainous terrain. (Feyisa et al. 2014) proposed the automatic water extraction index (AWEI) to identify water features, which has two conditions: AWEIsh is designed primarily to remove shadow pixels, while AWEInsh is intended for urban background areas. Similarly, vegetation indices have also been used to extract water features (Rokni et al., 2014).

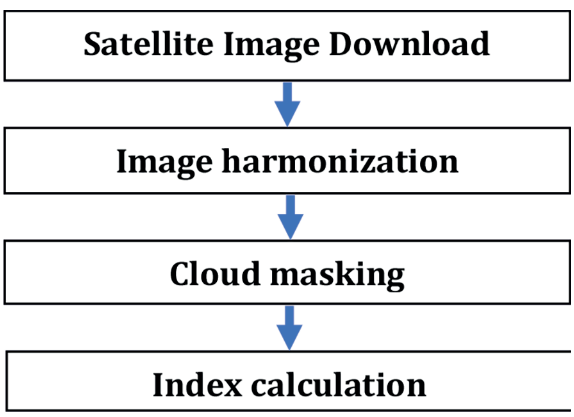

Fig. 2. The preparation of the data

Extraction of water surfaces by combining indices and thresholds

The thresholding method is relatively fast and straightforward to use. It is widely used for the identification of water features (Frazier et al., 2000; Fisher et al., 2016). The method we used is based on the combination of the four indices mentioned above to extract the water surface of the Al Massira Dam lake. A script was developed using the R software to perform this treatment. Thereafter the calculation of the surface was operated by a transformation of the raster images into metric surfaces. The thresholds used for the selected indices are: MNDWI >=0, NDWI >=0, NDVI <=0, AWEI >=0.

Table 2. OLS regression coefficients for harmonizing the TM and ETM+ bands with the OLI bands

Coefficient	Blue	Green	Red	NIR	SWIR1	SWIR2
Intercept	0.0003	0.0088	0.0061	0.0412	0.0254	0.0172
Scope	0.8474	0.8483	0.9047	0.8462	0.8937	0.9071

Table 3. Indices used for the evaluation of the surface of the lake of the dam Al Massira

Indexes	Formulas	Authors
NDVI	(NIR-Red) / (NIR+Red)	Rousse et al., 1973
NDWI	(Green-NIR)/(Green+NIR)	McFeeters S.K., 1996
MNDWI	(Green-SWIR1)/ (Green + SWIR1)	Xu H, 2006
AWEI	Blue +2.5*Geen-1.5 *(NIR+SWIR1)-(0.25*SWIR2)	Feyisa G.L. et al., 2014

Note: NDVI – normalized difference vegetation index, NDWI – normalized difference water index, MNDWI – modified normalized difference water index, AWEI – automatic water extraction index.

Models for predicting the dam's water storage and its lake area

To assess the relationship between the dam's lake area and the volume of water stored (impoundment), these two parameters were correlated. The R and Excel software are used to examine this relationship. In addition, to find out which model predicts this relationship better, the performance of four models was evaluated, including: exponential, linear, power, and polynomial. The accuracy of the estimation models was assessed by the coefficient of determination (R^2), the mean error (ME), and the root mean square error (RMSE). Lower values of ME and RMSE and higher values of R^2 indicate a better fit by the model.

RESULTS AND DISCUSSION

Evolution of the Oued Oum Er-Rbia water supply to the al Massira dam

The Oum Er-Rbia River is the only surface water resource of the Doukkala irrigated area. The evolution of hydrological inputs from the Oum Er-Rbia River to this dam, since the 1938-1939 crop year (82 years), is presented in Figure 3. Overall, there is a continuous downward trend in inputs. The average inflow is 2.05 billion m^3 with a coefficient of variation (CV) of about 64%, which indicates a large interannual variability. The inflows had a maximum of 7.25 billion m^3 in 1962–1963 and a minimum of 0.012 billion m^3 in 2013–2014. Two periods characterize the inflows during the 82 crop years. A period from 1939 to 1980 is characterized by water inflows (average of 3.2 billion m^3) above the general average and a second period from 1980 to 2020 is characterized by water inflows (average of 0.8 billion m^3) below the general average.

The analysis of water inflows shows a significant and continuous decrease during the 82 crop years. The deficit in water input of Wadi Oum Er-Rbia has been more marked during the last four decades. This reduction in inflows has resulted in shortages in the availability of this resource for the Doukkala irrigated area.

As shown in Figure 4, the average monthly inflows varied from 76 to 335 million m^3. These inflows are distributed according to the following: 19% of inflows are between the months of September and December, 71% of inflows are between February and June and 9% are between the months of July and September. The peak of the inflows is recorded during May.

Evolution of the Al Massira dam reservoir

The Al Massira Dam reservoir, measured in situ, fluctuated significantly from 1999 to 2021. Indeed, it has experienced a variation of 264 to 2616 million m^3. The average retention is 1145 million m^3 with a coefficient of about 73%, indicating a large variability.

As shown in Figure 5, the reservoir has undergone three distinct phases, during which remarkable variations are recorded. A phase of decline from 1999–2000 to 2008–2009 when it went from 1636 to 270 million m^3. This phase was followed by a very significant recovery during the 2009–2010 crop year when the reservoir rose to 1972 million m^3. Another phase of decline is also observed as of the 2016–2017 crop year where

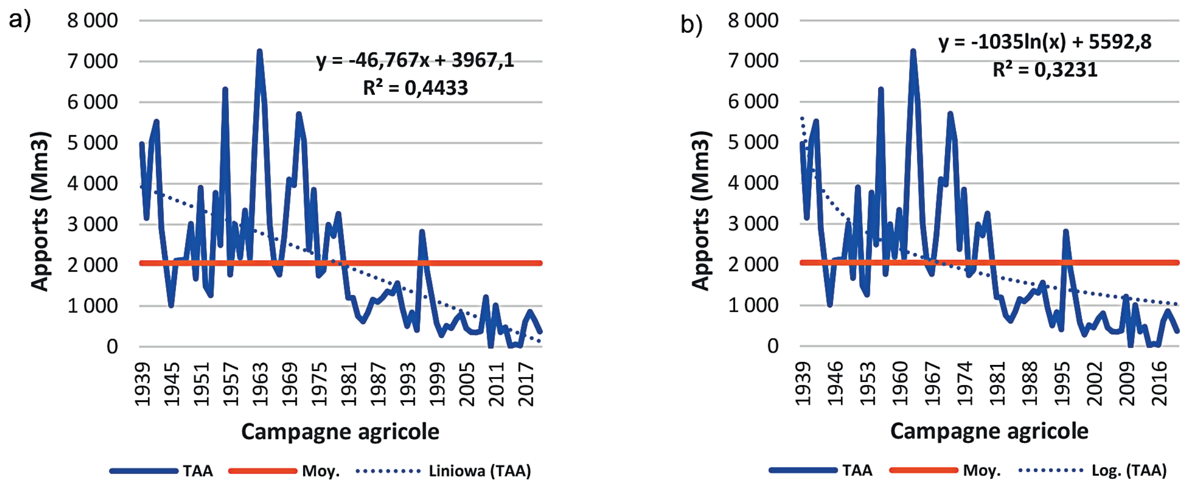

Figure 3. Evolution of water inflows from the Oum Er-Rbia River to the Al Massira dam

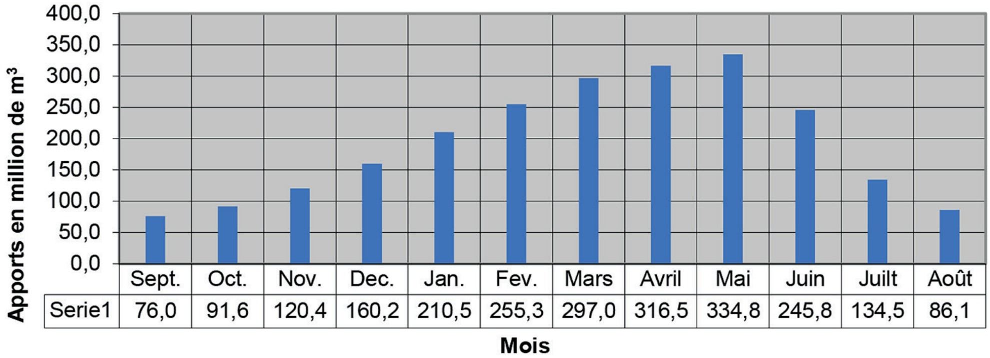

Figure 4. Average monthly evolution of the Oued Oum Er-Rbia water inflow to the Al Massira dam (82 years)

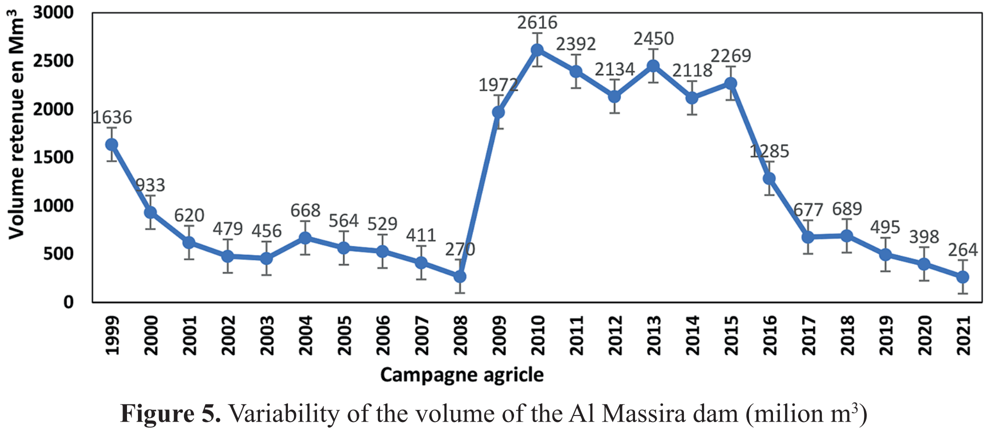

Figure 5. Variability of the volume of the Al Massira dam (milion m³)

the reservoir fell from 1285 to 264 million m³. Overall, this analysis shows a downward trend in the water resources of the dam.

Use of satellite images for the evaluation of the surface of the lake of Al Massira dam

As visually shown by the raster images resulting from the satellite images of Landsat, presented in figure 6, the surface of the lake of the dam Al Massira also experienced three distinct situations during the last two decades. A period of reduction of the surface going from 1999 to 2007, a period of increase of the surface from 2008 and another period of fall going from 2014 to 2021. The satellite images presented below give a visual overview of the evolution of the surface of the Al Massira dam.

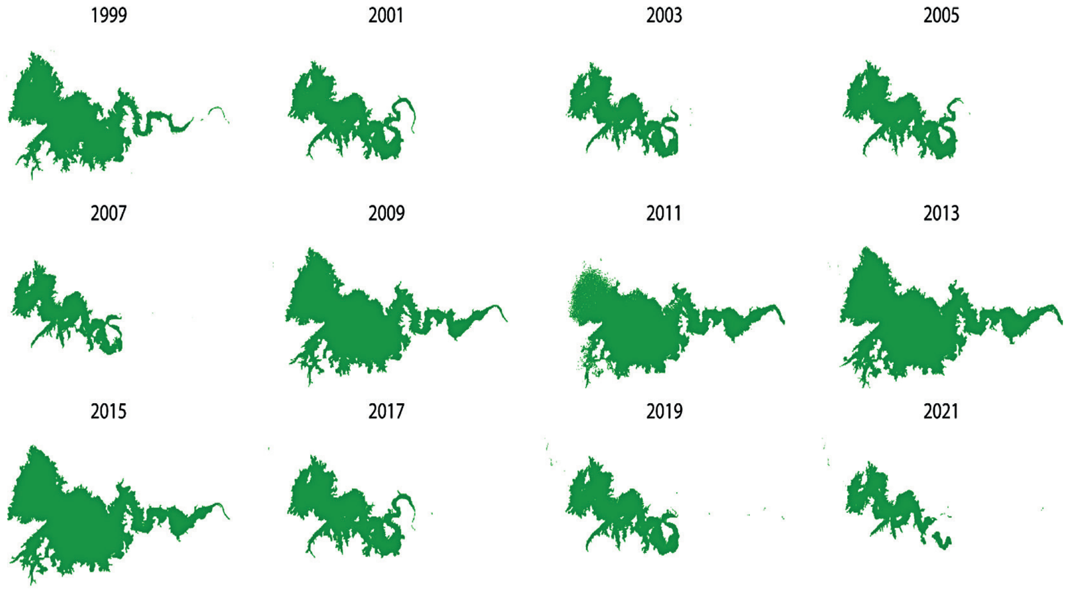

Figure 6. Temporal evolution of the Al Massira dam lake area

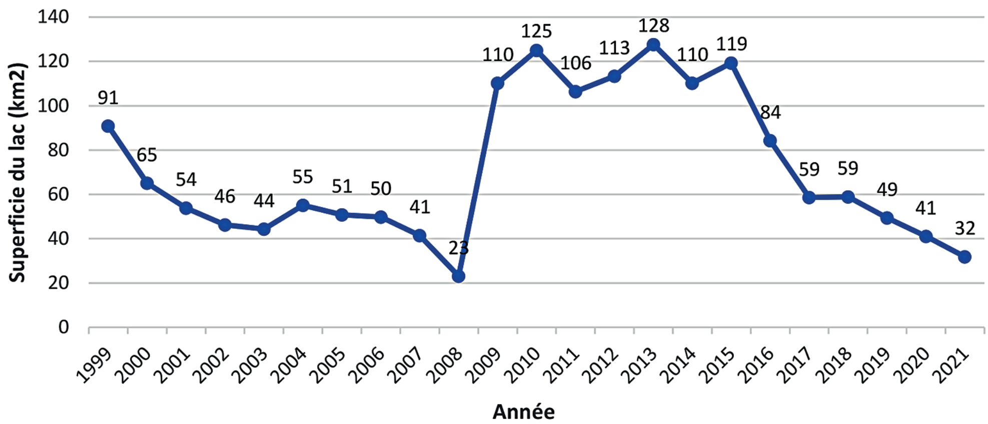

Figure 7. Evolution of the surface of the Al Massira dam lake

Evaluation of the surface of the lake of the Al Massira dam from 1999 to 2021

The calculation of the surface of the dam Al Massira was approached by the combination of the indices and the retained thresholds. The analysis was carried out by the R software. The results obtained after the transformation of raster images into digital surfaces show that the lake's average surface of the Al Massira dam during the selected period from 1999 to 2021 is 72 km^2 with a minimum of 23 km^2 and a maximum of 128 km^2. The coefficient of variation is relatively high (CV = 42%), which shows great interannual variability. This area has been reduced by 73% between 2015 and 2021.

The evolution of the surface area of the lake of the dam knows an overall downward trend (Figure 7). At the same time, strong demand for water in the region continues to increase due to the expansion of irrigated agriculture and the growing needs of major cities such as Casablanca, Safi, Sidi Bennour, El Jadida and by the planned transfer of water to the city of Marrakech.

Relation between the surface of the lake of the Al Massira dam and its water retention

Relation between the surface of the lake of the dam and its water retention

To study the relationship between the surface area of the Al Massira dam lake determined by spatial remote sensing and its water retention measured in situ, a correlation between these two parameters was established. The results obtained revealed a strong positive correlation between the two variables. Indeed, the correlation coefficient obtained is r = 0.97.

Table 4. Comparison of the performance of the prediction models

Models		ME	RMSE	R^2
Exponential:	$y = 170.53e^{0.0227x}$	13.24	208.25	0.97
Linear	$y = 17.381x$	107.23	293.84	0.87
Power	$y = 1.2671x^{1.5671}$	-20.39	122.95	0.97
Polynomial	$y = 0.1205x^2 + 5.4883x$	2.86	117.52	0.98

Similar results were found by El Orfi et al. in 2020 during a study conducted in Morocco on the Ahmed El Hansali dam. Indeed, this study showed that the water volumes estimated by spatial remote sensing, using the MNDWI (Modified Normalized Difference Water Index), are similar to the volumes estimated in situ by the Oum Er Rbia Hydraulic Basin Agency. The coefficient of determination R^2 was 0.90 (El Orfi et al, 2020).

This relationship confirms the performance of the combination approach of indices and thresholds, used for the calculation of the lake area of the dam. Therefore, it can be said that the surface water distribution can be accurately calculated using the combination of spectral indices.

Models for predicting dam impoundment as a function of dam lake area

Given the strong correlation between dam impoundment and lake area (r = 0.97), it is possible to proceed with the selection of a model that best predicts this relationship. For this purpose, several prediction models were used to select the best one.

The models chosen are exponential, linear, power, and polynomial. The performance of the models is judged by the accuracy parameters, namely the ME (mean error), the RMSE (root mean square error), and the R^2 (coefficient of determination).

The results show a better yield of the polynomial model's performance than the other models. It can be said that it is the model with the best accuracy parameters. It is the model that presents the lowest RMSE (117.52), the ME (2.86) that is close to 0 and the R2 (0.98) that is the highest (Table 4, Figure 8). Therefore, it is the model of prediction par excellence of the Al Massira dam reservoir according to the area of its lake determined by spatial remote sensing.

The monthly impoundments of the Al Massira Dam could therefore be determined using the

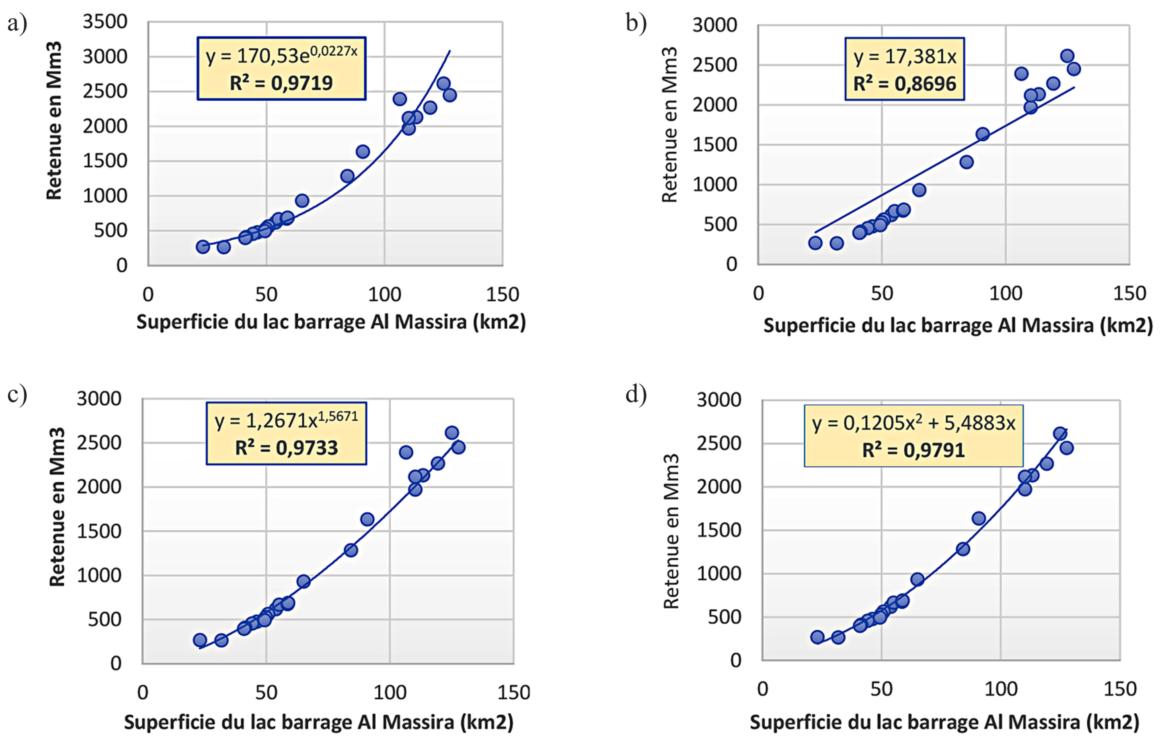

Figure 8. Prediction models for dam impoundment as a function of its lake area: (a) exponential model, (b) linear model, (c) power model, (d) polynomial model

monthly areas of the dam lake determined by exploiting the contribution of satellite images and the polynomial model that establishes the relationship between the two parameters instead of manually assessing them in situ.

This approach to monitoring the dam impoundment demonstrates the importance of combining in situ and geospatial assessment methods. Geospatial methods and techniques can therefore be complementary to conventional methods. They also allow a gain in terms of time and cost of information production.

Given these results, these methods can be integrated into the information systems for monitoring surface water resources (dams, lakes) on a regional and national scale to produce relevant information for monitoring and steering.

CONCLUSIONS

The Moroccan agricultural sector is very much linked to surface and ground water availability and climatic conditions. The Doukkala irrigated perimeter, served by water stored at the Al Massira dam, is currently experiencing an increasingly serious water shortage. The present study has revealed a continuous regression of the availability of this resource during the last decades. The causes of this regression are multiple and related much more to climatic conditions and bad practices of use of users.

The characterization of the evolution of the water resource's availability at this dam's level was carried out in the map of the study by exploiting the data measured in situ and the use of satellite images as a new alternative to evaluate this availability. The Landsat satellite images were used to assess the lake's surface area of the Al Massira Dam by adopting an approach combining vegetation indices and thresholds for the calculation of the surface area of the dam lake. Then the existing relationship between the Al Massira Dam lake area determined by spatial remote sensing and its water retention measured in situ was examined. The results obtained revealed a strong positive correlation between the two parameters. Indeed, the correlation coefficient obtained is of the order of $r = 0.97$. This relationship confirms the performance of the adopted approach.

Subsequently, the aoutors were interested in finding the best model for predicting the dam's retention as a function of its lake. The second-degree polynomial model showed a better performance. It is the model for which we recorded the lowest RMSE (117.52), the ME (2.86) which is close to 0 and the R^2 (0.98) the highest. It can therefore be said that it is the model with the best accuracy parameters and thus it is the model of prediction par excellence of the Al Massira dam reservoir according to the area of its lake determined by spatial remote sensing.

This approach to monitoring the dam reservoir demonstrates the importance of combining in situ and geospatial assessment methods. Geospatial methods and techniques can be complementary to conventional methods. They allow a gain in terms of time and cost of information production. Therefore, these methods must be integrated into the information systems for monitoring surface water resources (dams, lakes) at the local, regional and national levels to produce relevant information for monitoring and steering and to produce databases that are very useful for managers to make appropriate decisions.

REFERENCES

1. Agence du Bassin Hydraulique de l'Oum Er-Rbia (ABHOER) 2012. Projet de Plan Directeur d'Aménagement Intégré des Ressources en Eau du Bassin de l'Oum Er-Rbia et des bassins côtiers atlantiques. Rapport de présentation.
2. Fisher A., Flood N., Danaher T. 2016. Comparing Landsat water index methods for automated water classification in eastern Australia, Remote Sens. Environ, 175–167.
3. Bounif M., Rahimi A., Bouassria A., El Mjiri I. 2021. Study of agricultural land use variability in Doukkala irrigated area between 1998 and 2020," 2021 Third International Sustainability and Resilience Conference: Climate Change, 2021, 170–175. DOI: 10.1109/IEEECONF53624.2021.9667965
4. Roy D.P. et al. 2016. Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. Remote Sens. Environ., 185, 57–70. DOI: 10.1016/j.rse.2015.12.024
5. Vermote E., Roger J.C., Franch B., Skakun S. 2018. LaSRC (Land Surface Reflectance Code): Overview, application and validation using MODIS, VIIRS, LANDSAT and Sentinel 2 data's, in IGARSS 2018 – 2018 IEEE International Geoscience and Remote Sensing Symposium, 8173–8176. DOI: 10.1109/IGARSS.2018.8517622.
6. ECS: Water Resources of Nepal in the Context of Climate Change, 2011. http://www.wecs.gov.np/

uploaded/water-recource-climate-change.pdf.

7. Feyisa G., Meilby H., Fensholt R., Proud S.R. 2014. Automated Water Extraction Index: a new technique for surface water mapping using Landsat imagery. Remote Sens. Environ., 140, 23–35.
8. Feyisa G.L., Meilby H., Fensholt R. 2014. Proud, S.R. Automated water extraction index: A new technique for surface water mapping using Landsat imagery. Remote Sens. Environ, 140, 23–35.
9. Feyisa G.I., Meilby H., Fensholt R., Proud S.R. 2014. Automated Water Extraction Index: A new technique for surface water mapping using Landsat imagery, Remote Sensing of Environment, 140, 23–35.
10. Alaoui L., Agoumi A., Moncef M., Mokhliss K. 2000. Étude du régime thermique de la retenue Al Massira (Maroc). Hydroécol. Appl., 12(1–2), 183–206.
11. Masocha M. et al. 2018. Surface waterbodies mapping in Zimbabwe using Landsat 8 OLI multispectral imagery: a comparison of multiple water indices. Phys. Chem. Earth, 63–67.
12. Ministère d'Equipement et de l'Eau, 2022. Site web officiel. http://81.192.10.228/patrimoine/barrages/situation-journaliere-des-principaux-grands-barrages.
13. MAPMDREF. 2019. Agriculture en chiffres en 2018.
14. McFeeters S.K. 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. Int. J. Remote Sens., 17, 1425–1432.
15. ORMVAD, 2020. Rapports d'activités annuels et de gestion de l'ORMVA des Doukkala, El Jadida, Morocco, 2010 à 2020.
16. Arreola-Esquivel M., Delgadillo-Herrera M., Toxqui-Quitl C., PadillaVivanco A. 2019. Index-based methods for water body extraction in satellite data. Proc. SPIE 11137, Applications of Digital Image Processing XLII, 111372N, September 2019. DOI: 10.1117/12.2529756
17. Palmer S.C., Kutser T., Hunter P.D. 2015. Remote sensing of inland waters: challenges:
18. Progress and future directions. Remote Sens. Environ., 175, 1–8.
19. Frazier P.S., Page K.J. 2000. Photogrammetric Engineering & Remote Sensing, 66(12), 1461–1467.
20. Rokni K., Ahmad A., Selamat A., Hazini S. 2014. Extraction des caractéristiques de l'eau et détection des changements à l'aide de l'imagerie Landsat multitemporelle. Remote Sens, 6, 4173–4189.
21. Harbouze R., Pellissier J.-P., Rolland J.-P., Khechimi W. 2019. Rapport de synthèse sur l'agriculture au Maroc. [Rapport de recherche] CIHEAM-IAMM, 104.
22. Rouse J.W., Haas R.H., Shell J.A., Deering D.W. 1973. Monitoring Vegetation Systems in the Great Plains with ERTS. In Proceedings of the Third Earth Resources Technology Satellite-1 Symposium, Washington, DC, USA 1973, 309–317.
23. Tri Dev Acharya, Anoj Subedi, He Huang, and Dong Ha Lee, 2019: Application of water indices in surface water change detection using landsat imagery in Nepal. Sensors and Materials, 31(5), 1429–1447.
24. El Orfi T., El Ghachi M., Lebaut S. 2020. Contributions of remote sensing in the diachronic study of the spatial and temporal evolution of the Ahmed El Hansali dam water reservoir from 2002-03 to 2018-19. E3S Web of Conferences, EDP Sciences, 183, 02004.
25. Zhou, Y., et al. 2017. Open surface water mapping algorithms: a comparison of water related spectral indices and sensors. Water, 9(256), 1–16.
26. Xu H. 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int. J. Remote Sens., 27, 3025–3033.
27. Zhu Z., Wang S., Woodcock, C.E. 2015. Improvement and expansion of the Fmask algorithm: Cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images. Remote Sens. Environ., 159, 269–277. DOI: 10.1016/j.rse.2014.12.014