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Dear Dr Mazvimavi,

Please find in the following the revised version of our manuscript “Monitoring small reservoirs storage from satellite remote sensing in inaccessible areas”. We really appreciate the feedbacks provided by T. Francke, W. Gumindoga and an anonymous referee. Their comments and suggestions are first presented with our responses and proposed corrections to the manuscript, and a marked-up manuscript version is then given with all modifications.

Sincerely,

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### **Response to the Short Comment 1 posted by Till Francke.**

*The manuscript by Avisse et al. describes an elaborated approach for retrieving the storage volumes of smaller reservoirs from remote sensing. As it relies exclusively on well-available optical and DEM data, it seems a valuable contribution for the monitoring of these storages in data-scarce regions. Since the authors also emphasise the general usefulness and transferability in this regard, I'd like to encourage them to share the required source code of the algorithm, which would match the spirit of publishing in an Open-Access-journal.*

We thank you for your constructive comments. We indeed think this method could be applied to other reservoirs in different parts of the world.

**We took your suggestion to make the code available (see [code and data availability](#)); it is now possible to download it at <https://drive.google.com/open?id=0B54cRCK06X-9RUdqaTZmWkdsOXc>.**

*Further minor suggestions: - Fig. 10 suggests that the methods tends to underestimate large volumes. Especially for Karama and Tanour there seems to be a upper limit, which the predictions of the method do not exceed. This is apparently not related to the complete filling of the reservoirs, as the ground observations confirm some dynamics within these phases. Is there any explanation to that?*

This is a good point. We think that this phenomenon may be caused by a very small variation of the water area for highest water levels. If the number of high-elevation pixels is small, the uncertainty on their corrected elevation (and thus the filling curve) can potentially affect the estimate of the maximum storage. This may indeed be a limitation of the method.

**We added the following sentences in the revised version of the paper (p14, l13): “For some reservoirs (i.e., Karama and Tanour), the method seems to have difficulties to predict highest storages. Indeed, if the number of high-elevation pixels is small, the uncertainty on their corrected elevation (and thus the filling curve) can potentially affect the estimate of the maximum storage. This may be a limitation of the method.”**

*- Table 2: The values of  $eps_m(V)$  for Kafrein and King Talal differ surprisingly from the impression one gets in Fig 10: In the plot, Kafrein seems to be modelled much better than King Talal. Is there any explanation for this surprising impression?*

The selected error indicator does not represent well the quality of the results. This is due to the definition of  $eps_m(V)$  itself.  $eps_m(V)$  measures the ratio of errors compared to observed storages. Errors for Kafrein reservoir estimates are low, but the storage is also sometimes very low. This explains why the relative error is high. For King Talal, observed storages are systematically higher than estimated ones, which may explain why  $eps_m(V)$  tends to be so small.

**Proposed correction: We replaced  $eps_m$  with the NRMSE criteria (p17, l5) defined as:**

$$NRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N \frac{(RS_i - Hist_i)^2}{N}}}{Hist_{max} - Hist_{min}}$$
 to give more weight to large errors than to smaller ones. The normalisation is also done by considering ( $V_{max} - V_{min}$ ) to consider the large amplitude of storage variations. By using this criteria, errors vary between 10 % and 16 % for V and between 5 % and 30 % for H, and better match the impression we have when looking at the curves.

- Specifying a relative error for H ( $eps_m(H)$ , Table 2, Fig.11) does not make sense to me: If H is water surface elevation,  $eps_m$  will then depend on absolute altitude. Instead, water level ( $H - H_{min}$ ) or absolute deviation ( $H_{RS} - H_{HIST} - \text{mean}(H_{RSH\_HIST})$ ) should be used.

Yes, you are right. We did not make it clear enough in the first version of the manuscript, but we did use ( $H_c - H_{min}$ ) to calculate the relative error. In the definition that we chose for the NRMSE, the normalisation is now done using the difference between maximal and minimal values, so we do not have this issue anymore.

- The choice of the regression used for reconstructing the H-A-relationship is not explained: According to Tab. 1, "Polynomial Regression" of different order and "Local Polynomial Regression" are used. Are they selected by best fit? The respective description (p. 10, ll. 15) is quite vague, especially concerning the 3-fold repetition of the process and the exclusion of outliers.

**Proposed correction (p11, l4):** "To address the issue, a polynomial regression on observed land pixels ( $A > A_i$ , with  $A_i$  the area assumed as immersed during the satellite elevation retrieval) is used to build a "corrected elevation"-area relationship ( $A \rightarrow H_c(A)$ ) that **best fits the data (on a least-squares sense)**. **Values of H greater than the 80<sup>th</sup> or lower than the 20<sup>th</sup> percentile are ignored to filter potential errors and smooth the data.** This step is executed three times – one for each DEM – and the better quality dataset (i.e., the one with less dispersion and "anomalies" as defined above) is kept. Examples are shown in Fig. 8."

- When discerning water surfaces, water bodies with macrophyte growth remain a serious challenge. It would be interesting to discuss if the presented approach for eliminating the SLC-data gaps could also help to tackle this issues.

Macrophytes could indeed put a limitation to the detection of water bodies area. If there is no significant variation in the elevation, the 3D correction will not be as effective as with the Landsat N/A stripes to fill macrophyte-covered water areas. However, in that case the missing volume may not be significant if macrophytes do not cover a large part of the reservoir.

*- The figures containing map mostly refer to a certain datum/projection. Still, this would need the specification of some units [km]; a scalebar would facilitate interpretation.*

Thanks for this comment. We indeed forgot to specify that 1 unit equals 1 m.

**It has been added in the legend of figures 1, 3, 4, 7 and 9.**

*- Commonly, table captions are displayed above a table, not below it.*

This is unfortunately out of our hands as we used the HESS Discussion template which defines the standards.

**Response to the Referee Comment 1 posted by Anonymous Referee 1:**

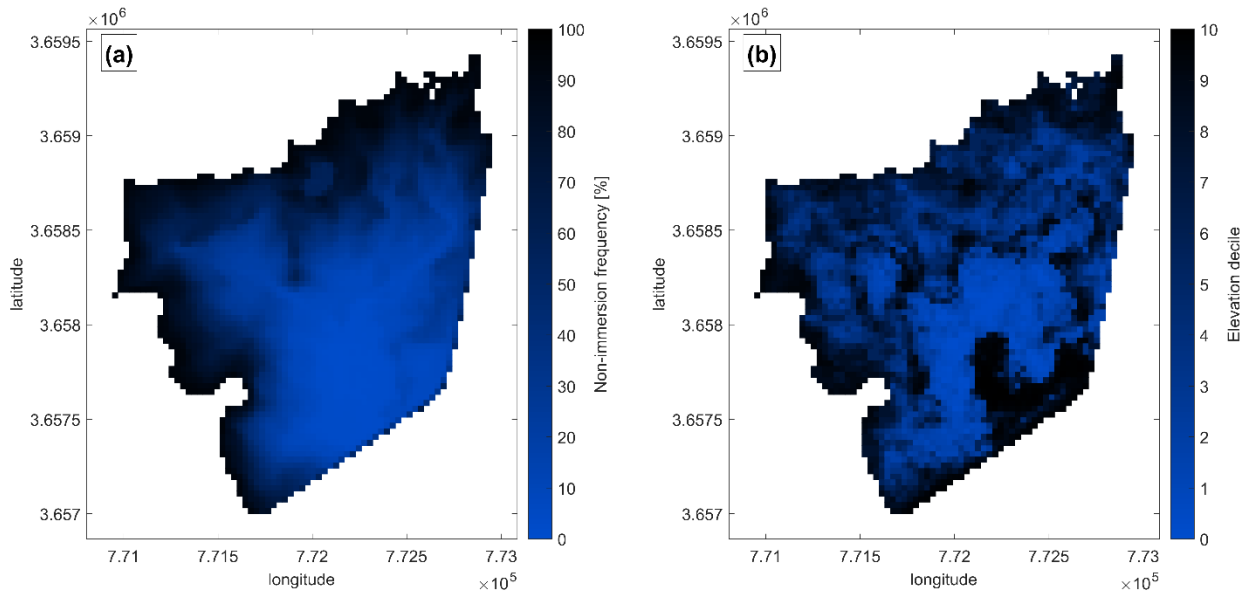
The manuscript by Avisse et al. presents a novel approach to derive water level and water storage of small reservoirs based on optical images and DEMs. The methodology is a potentially valuable supplement to satellite altimetry, which traditionally is used for water level estimation and the results presented in the manuscript are promising. The paper is generally well written and well organized. I have some comments that are specified below.

Thank you for your time and your helpful comments. We indeed think that this method complements well current methods based on satellite altimetry to monitor more reservoirs, and to conduct studies for periods during which satellite altimetry did not permit to estimate small reservoir storage variations.

General comments:

Section 2.2.2 that describes the elevation-area relationship needs to be more detailed possibly supplemented with illustrations in the same way as section 2.1 and figure 4 to enhance the understanding. E.g  $r^q$  is not explained and step 3 is quite vague.

**- We have added the following figure (p11):**



**“Figure 7: (a) Relative non-immersion frequency ( $1 - r^p$ , from the 2D classes) and (b) elevation (from the DEMs, in terms of decile) in the Kudnah reservoir. Coordinates are expressed in CRS WGS 84 / UTM zone 36N, in which 1 unit equals 1 m.”**

**Proposed additional comment (p10, 19):** “To illustrate the interest of this section, Figure 7 shows both  $r^p$  and the relative elevation in the Kudnah reservoir. We can see that the two do not always match as we would expect – i.e. lowest pixels are not always the most frequently immersed, nor are the highest

pixels the most rarely immersed. The immersion frequency ( $r^p$ ) can actually be used to correct the elevation. The former, which is estimated from the results of the 2D classification enhancement, is indeed assumed more reliable than the original DEM. Hence, each pixel's elevation  $H^p$  is put in relation with the area  $A^p$ , defined as the cumulated area of all pixels  $q$  in the reservoir for which  $r^q \geq r^p$ . The examples of Fig. 8 confirm the observations made on Fig. 7: pixels' elevations are not always correlated with the number of times they are classified as water. To a certain extent the difference was expected from the DEM's low vertical precision, but some "anomalies" concerning the most often immersed pixels (i.e. lowest  $A^p$ ) can be recurrent from one reservoir to another due to either a strong dispersion in elevation (see SRTM-X data in Fig. 8 (b)), or a flat elevation (see SRTM-C data in Fig. 8 (c))."

-  $r^q$  is given in Equation 1 (p 10). Indeed, by replacing  $p$  with  $q$  (for all other pixels in the reservoirs), we get:

$$r^q = \frac{N_{water}^q}{N_{water}^q + N_{land}^q}$$

where  $N(q, water)$  is the number of times the given pixel  $q$  is counted as Water, and  $N(q, land)$  the number of times it is counted as Land. Images where the pixel  $q$  is classified as Unknown are ignored.

**Proposed correction (p10, l13):** "Each pixel's elevation  $H^p$  is put in relation with the area  $A^p$ , defined as the cumulated area of all pixels  $q$  in the reservoir for which  $r^q \geq r^p$ ."

- We realised step 3 was not clear enough with the first short comment published by T. Francke in the open discussion. We thus added several corrections to detail each part of step 3 (see above also).

**Proposed correction (p11, l4):** "To address the issue, a polynomial regression on observed land pixels ( $A > A_i$ , with  $A_i$  the area assumed as immersed during the satellite elevation retrieval) is used to build a "corrected elevation"-area relationship ( $A \rightarrow H_c(A)$ ) that **best fits the data (on a least-squares sense)**. **Values of  $H$  greater than the 80<sup>th</sup> or lower than the 20<sup>th</sup> percentile are ignored to filter potential errors and smooth the data.** This step is executed three times – one for each DEM – and the better quality dataset (i.e., the one with less dispersion and "anomalies" as defined above) is kept. Examples are shown in Fig. 8."

*Please quantify or at least discuss the error on your estimated water levels/volumes.*

Identifying the cause to the errors of the method is indeed fundamental for further research on reservoir monitoring using DEM. The errors associated with the elevation-area relationships must be found in the DEMs' low vertical precision: up to 15 m for 90 % of the data for SRTM-C, 6 m for 90 % of the data for SRTM-X, and a standard deviation of 8.68 m for the ASTER dataset (p9, l16). Errors on the corrected elevation are difficult to quantify from the curves presented in Fig. 7, as we do not know the error that should actually be expected for each reservoir's location. All we can derive from the area-elevation relationships is that "pixels' elevations are not always correlated with the number of times they are classified as water [because of the] DEM's low vertical precision" (p10, l15-17).

This is the reason why we can only quantify changes in the reconstruction of water bodies area (see Table 3) and measure the error on water levels and volumes after all correction steps are completed (see Table 2). We cannot decompose the error and associate each part to a certain step without making unfounded assumptions. The discussion on the error of the results is given on p14, l5 to p17, l14.

*specific comments:*

*P 2, l 10-16: The authors mention satellite altimetry. The authors could here mention the newer SAR missions CryoSat-2 and Sentinel-3, which have an along-track resolution of 300 m. The CryoSat-2 mission in SAR mode has demonstrated the potential of monitoring small lakes. Altimetry is not just limited to a few 100 lakes.*

Yes, you are right, we forgot to mention these satellites. They indeed provide large improvements in terms of resolution. The reference to the few hundred large lakes and reservoirs on the planet actually comes from a statement made by Gao et al. (2012) – also mentioned in Zhang et al. (2014). But the more recent satellites mentioned by the reviewer clearly increased the potential monitoring of water level to thousands of lakes and reservoirs (Crétau et al. 2016).

However, Cryosat was initially designed to monitor the thickness of Arctic ice, and SAR and SARin modes are only available over a limited surface of the Earth (mainly high latitudes and mountain glaciers, see European Space Agency (2012)). Its revisit cycle of 369 days also impedes the monitoring of small reservoirs on a monthly basis. Moreover, the inter-track of  $\approx 7$  km and  $\approx 52$  km at the equator for CryoSat-2 and the two Sentinel-3 satellites respectively (Donlon et al., 2012; Crétau et al., 2016) still make many small reservoirs out of the trajectory of the nadir-viewing sensors onboard.

It can be noted that Crétau (2016) also summarised errors on measurements estimates for a set of lakes and reservoirs of various size and location to highlight the fact that many elevation measurements over a water body are necessary to get a precise estimate. Zhang et al. (2014) estimate that a distance of 10 km is necessary to take enough measurements to get a precise elevation assessment with “older” satellite altimeters (i.e. with an along-track path resolution of 1 km). By considering the same ratio of measurements per distance crossed, the width of reservoir bodies observed by satellites like Sentinel-3 (i.e., resolution of 300 m) still needs to reach 3 km, which is larger than most reservoirs considered in our study – assuming that the satellite passed at the right location over them.

Then, for these reasons and as attested to by research studies that used these satellites, the focus has been made on reservoirs larger than 100 km<sup>2</sup> (Crétau et al., 2016; Jiang et al., 2017) or rivers that stretch over several hundred kilometres (Villadsen et al., 2015).

**Proposed correction (p2, l11):** “They have a high vertical accuracy with root-mean-square errors on the order of centimetres to tens of centimetres depending on the altimeter and the size of the water body (Calmant et al., 2008; Crétau et al., 2016). Yet, **the above-mentioned** sensors are affected by important drawbacks, including nadir viewing, narrow swath, coarse cross-track spacing (a few hundred kilometres), long along-track path length (about 1 km), large elevation differences around some water

areas, that impede their application to more than a few hundred large lakes and reservoirs on the planet (i.e. area > 100 km<sup>2</sup> and width > 500 m) (Crétaux and Birkett, 2006; Alsdorf et al., 2007; Gao et al., 2012). **More recent satellites such as Cryosat-2 or Sentinel-3 present significant improvements in terms of along-track resolution (≈300 m). However, their respective inter-track of 7 km and 52 km (Donlon et al., 2012; Crétaux et al., 2016) still place many reservoirs out of the trajectory of their nadir-viewing sensors onboard. The small inter-track of Cryosat is also realised at the expense of a long revisit cycle (369 days) that impedes any monitoring of small reservoirs on a monthly basis.**

**Proposed additional precision in the introduction (p1, l5):** “This paper proposes a novel approach using Landsat imagery and Digital Elevation Models (DEM) to retrieve information on storage variations in **any inaccessible region.**”

**Proposed additional precision for the conclusion (p20, l15):** “For all “uncovered” small or large reservoirs, the uses of datasets available over the whole continental surface **make this method a valuable complement to satellite altimetry to increase the number of reservoirs observable anywhere in the world.** The thresholds dynamically defined for both the 2D enhancement and the 3D reconstruction **also** make the method potentially suitable to monitor reservoirs in **truly** inaccessible areas.”

*Eqn (3): As pointed out in the short comment Eqn (3) does not make sense and yes NRMSE is a good solution.*

We thank you for this response to the first interactive comment. We consider your advice and keep the NRMSE criteria to quantify the error of our estimates.

*P 13, l8-10: "We can see coherent storage variations through the presence of drawdown-refill cycles, which means that the 2D enhancement and 3D reconstruction steps have improved the detection of water and helped to overcome the low Landsat repeat cycle of 16 days." I do not see this connection. How do you see that you improved the water detection when you are not comparing to anything?*

Yes indeed, this argument alone does not make sense. Thank you for noticing the mistake. Changes in water bodies' area obtained with similar tools – but without the 2D enhancement and 3D reconstruction – are available in the supporting information (Figure S3) of the study conducted by Müller et al. (2016). Improvements in the detection of annual drawdown-refill cycles are particularly clear for Sahwat al-Khadr and Roum dams.

**Proposed correction (p14, l6):** “By qualitatively comparing our results to those obtained by Müller et al. (2016) (monitoring of Syrian reservoirs using Landsat 7 datasets but before the 2D and 3D corrections), we can see more coherent storage variations through the presence of **annual** drawdown-refill cycles – **particularly for Roum and Sahwat al-Khadr.** It means that the 2D enhancement and 3D



reconstruction steps have improved the detection of water and helped to overcome the low Landsat repeat cycle of 16 days.”

*P 14, l1-2. "Some of the differences between our estimates and measured data might then come from the inaccuracy regarding the data collection date". Is this because the in situ data are not daily?*

Yes indeed.

**Proposed correction (p14, l11):** “Reservoirs managed by Jordan are used to validate the method by comparing our remote sensing estimates of elevation and storage with **monthly** *in situ* measurements conducted by the Jordan Valley Authority (JVA).”

*Conclusion/Discussion: You could also mention the potential of Sentinel-1 and 2, which have a much higher resolution than Landsat.*

Yes indeed, thank you for mentioning these two satellites. Actually, as explained p2, l34, we chose to not detail SAR sensors as they have “been less used due to the difficulty to get consistent results, as the required condition of a significantly lower phase coherence of water areas than of the surrounding land surface is not always met with orbital repeat cycles of more than a few days, or with wind or rain (Alsdorf et al., 2007; Eilander et al., 2014)”.

**Proposed correction (p2, l33):** “Water surface areas are commonly determined from optical satellite imagery such as MODerate Resolution Imaging Spectroradiometer (MODIS) and Landsat products (Xiao et al., 2006; Gao et al., 2012), or Synthetic Aperture Radar (SAR) sensors (e.g., RADARSAT, JERS-1, ERS or Sentinel-1) (Annor et al., 2009; Duan and Bastiaanssen, 2013; **Amitrano, 2014**).”

With regard to Sentinel 2, new references are added in the introduction.

**Proposed correction (p3, l8):** “**The potential of the recent two Sentinel-2 satellites can also be mentioned for post-2015 studies. Launched in June 2015 (Sentinel-2A) and March 2017 (Sentinel-2B), they provide spectral bands at a resolution of 10 m for visible and NIR bands, and at 20 m for SWIR bands. They also have a repeat cycle of 5 days by combining the two (European Space Agency, 2013; Yang et al., 2017).**”

**Proposed additional correction for the conclusion (p20, l22):** “**The recent two Sentinel-2 satellites also promise a great improvement of the method for post-2015 studies, as they produce images with spatial and temporal resolutions finer than Landsat (up to 10 m and 5 days). Combining Landsat and Sentinel-2 satellites would then reduce the already short revisit cycle of water bodies and would provide near real-time updates on water bodies storage.**”

Furthermore, the algorithms used in the method automatically detect water bodies, define the water areas retrieval parameters, build filling curves and assess reservoir storage. **Such algorithmic tools can**

then be dynamically updated with each new image from Sentinel-2 and Landsat satellites, giving the model the potential to learn by itself and correct previous storage estimates while generating new ones. This approach is somehow comparable to the continuous change detection proposed by Zhu and Woodcock (2014).”

References added or not cited in the first version of the discussion paper:

Amitrano, D., Martino, G. D., Iodice, A., Mitidieri, F., Papa, M. N., Riccio, D., and Ruello, G.: Sentinel-1 for Monitoring Reservoirs: A Performance Analysis, *Remote Sensing*, 6, 10 676 – 10 693, doi:10:3390/rs61110676, 2014.

Crétaux, J.-F., Abarca-del Río, R., Bergé-Nguyen, M., Arsen, A., Drolon, V., Clos, G., and Maisongrande, P.: Lake Volume Monitoring from Space, *Surveys in Geophysics*, 37, 269 – 305, doi:10:1007/s10712-016-9362-6, 2016.

Donlon, C., Berruti, B., Buongiorno, A., Ferreira, M.-H., Féménias, P., Frerick, J., Goryl, P., Klein, U., Laur, H., Mavrocordatos, C., Nieke, J., Rebhan, H., Seitz, B., Stroede, J., and Sciarra, R.: The Global Monitoring for Environment and Security (GMES) Sentinel-3 mission, *Remote Sensing of Environment*, 120, 37 – 57, doi:10:1016/j:rse:2011:07:024, 2012.

European Space Agency: CryoSat Product Handbook, available at: [https://earth.esa.int/documents/10174/125272/CryoSat\\_Product\\_Handbook](https://earth.esa.int/documents/10174/125272/CryoSat_Product_Handbook), 2012.

European Space Agency: Sentinel-2 Mission Details, available at: <https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/sentinel-2>, 2013.

Jiang, L., Nielsen, K., Andersen, O. B., and Bauer-Gottwein, P.: Monitoring recent lake level variations on the Tibetan Plateau using CryoSat-2 SARIn mode data, *Journal of Hydrology*, 544, 109 – 124, doi:10:1016/j:jhydrol:2016:11:024, 2017.

Villadsen, H., Andersen, O. B., Stenseng, L., Nielsen, K., and Knudsen, P.: CryoSat-2 altimetry for river level monitoring – Evaluation in the Ganges-Brahmaputra River basin, *Remote Sensing of Environment*, 168, 80 – 89, doi:10:1016/j:rse:2015:05:025, 2015.

Yang, X., Zhao, S., Qin, X., Zhao, N., and Liang, L.: Mapping of Urban Surface Water Bodies from Sentinel-2 MSI Imagery at 10 m Resolution via NDWI-Based Image Sharpening, *Remote Sensing*, 9, doi:10:3390/rs9060596, 2017.

Zhu, Z. and Woodcock, C. E.: Continuous change detection and classification of land cover using all available Landsat data, *Remote Sensing of Environment*, 144, 152 – 171, doi:/10:1016/j:rse:2014:01:011, 2014.

**Response to the Referee Comment 2 posted by Webster Gumindoga (Referee 2):**

*I read with enthusiasm the paper by Nicolas Avisse et al on Monitoring small reservoirs storage from satellite remote sensing in inaccessible areas. The approach to use satellite data (Landsat imagery and Digital Elevation Models (DEM)) to retrieve information on storage variations in ungauged and inaccessible areas is welcome for improved water resource management.*

Thank you for your interest and for taking time commenting our paper.

*A question arises for the Fmask function for distinguishing land and water areas and producing a probability mask for clouds. What specific criteria was used to manually remove images that are almost entirely covered by clouds or with obvious large errors in water bodies detection? What specific quality control measures did the authors take to remain with 245 images per location? The authors can do justice by quantifying the uncertainty in the Fmask method.*

The analysis conducted to “manually remove images that are almost entirely covered by clouds or with obvious large errors in water bodies detection” (p6, l3) is a rough observation of Fmask classification results (mainly for categories ‘clouds’ and ‘water’ as mentioned above). The quality control is a visual comparison between these classification results and original images (SWIR-R-G for instance). Zhu et al. (2012) evaluate a cloud overall accuracy of 96.41 %, but it depends a lot on the satellite, location and time: Zhu et al. (2015) estimate an overall accuracy (i.e., for all classes) varying between 24 % and 89 %, for instance, depending on the Landsat 8 image chosen. Also, according to our study (p6, l8): “on average, 24.1 % of reservoirs’ pixels are misclassified as land, 8.1 % are covered with clouds or cloud shadows, and 8.6 % are in ‘N/A’ areas”.

In fact, the objective of this step is not to precisely detect clouds or water areas. We just need a first rough selection of images and remove those that could affect the next statistical analyses (statistical correction of elevation and 3D reconstruction through hidden areas). For instance, if Fmask detects clouds over the whole image, then it cannot be used in the next steps. Similarly, if Fmask classifies half an image as water, it is obviously a misdetection from the algorithm. By removing such images, we went from 300 to 245 images per location.

**Proposed correction (p5, l16):** “The algorithm was originally designed to separate potential cloud pixels from clear sky pixels on Landsat images using empirical thresholds on NDVI and the near-infrared band, **with an overall accuracy of 96.41 % (Zhu and Woodcock, 2012).**”

*In Section 2.1.3, how realistic is to define automatically the threshold for optimally distinguishing water bodies from clouds using the MNDWI technique?*

As the referee W. Gumindoga rightly points out, an automatic classification with MNDWI or NDVI (or any other criterion) will not give as good results as if we chose a specific criterion for each reservoir at each

time. A trade-off is indeed required between the time to spend on the detection and the quality of the results.

As explained in the introduction (p3, l11-24), various methods have been applied to detect water areas. The most basic ones rely on a predefined NDVI or MNDWI threshold, which is problematic for a multi-temporal analysis (Liu et al., 2012). Coltin et al. (2016) give an inventory of other indices generally used for detecting water, and advocate the implementation of automatic thresholds as they develop a supervised learning approach. Other methods rely on an automatic unsupervised classification (Wang et al., 2008; Gao et al., 2012). In our paper, we choose to automatically define a threshold for each image. Our protocol has actually the advantage of being entirely automatic (no further association between class and type of land use for instance). This approach is very fast, no selection of reservoir approximate location is required, and, as mentioned in the conclusion, it could “provide near real-time updates on water bodies storage”.

**Proposed additional reference (p3, l13):** “But determining an adequate value for a multi-temporal analysis can be challenging because such a threshold is known to be case-dependent (Liu et al., 2012; Coltin et al., 2016).”

**Other additional correction (p3, l17):** “To address these issues, decision tree defined thresholds have successfully been applied with various vegetation indices (e.g., Xiao et al., 2006; Islam et al., 2010; Yan et al., 2010), but remain case-dependent. **Coltin et al. (2016) have then advocated the implementation of automatic thresholds as they developed a supervised learning approach to improve flood mapping.**”

*Authors can also justify the selection of Landsat 7 images over the more recent Landsat 8, which do not have stripes after all.*

Yes you are right, Landsat 8 do have the advantage of not having stripes. We actually used all kinds of Landsat images including Landsat 8: “about 300 Landsat 4, 5, 7 and 8 images for each scene [...] are downloaded from the [USGS website]” (p5, l10). The goal is to use all Landsat images available to analyse changes in reservoir storage over long periods of time (ideally several decades), and Landsat 8 images are only available from February 2013.

*Section 3.1 what do the authors mean by saying “...some of the differences between our estimates and measured data might then come from the inaccuracy regarding the data collection date.”*

As pointed out by the Anonymous Referee 1, we did not mention that the “*in situ* measurements conducted by the Jordan Valley Authority” are monthly. Then, as these measurements are not automatically recorded, we do not know exactly on which day they were collected, and if they are always collected the same day in the month. Such uncertainty may change the difference between our estimates and measured data.

**We proposed the following correction when answering the Referee 1 comment (p14, l11):** “Reservoirs managed by Jordan are used to validate the method by comparing our remote sensing estimates of elevation and storage with **monthly** *in situ* measurements conducted by the Jordan Valley Authority (JVA).”

**Proposed additional correction (p15, l4):** “Because no information is available regarding the **data collection date**, some of the differences between our estimates and measured data might then come from **this lack of metadata.**”

*The authors need to improve on the equality of the maps by improving on some map fundamentals/basics such as north arrow, legend and scale.*

As pointed out by T. Francke in the Short Comment 1, we indeed forgot to specify that 1 unit equals 1 m for the scale.

**We have updated the legend of figures 1, 3, 4, 7 and 9. We have also added “latitude” and “longitude” for axis titles to match common representations of satellite images. The title “Inundation frequency” has also been added next to the colorbar in Figure 3.**

*Why not validating the elevation-area relationships with some established/measured rating curves*

We unfortunately do not have such relationships for Syrian nor Jordanian reservoirs. As the observed elevation and volume for Jordanian reservoirs do not represent the whole range of possibilities, and because few elevation measurements were available ( $15 \leq N \leq 35$ , see p17, l14) and not necessarily conducted at the same time as storage measurements, the relationships could not be retrieved with precision.

**New reference:**

**Coltin, B., McMichael, S., Smith, T., and Fong, T.: Automatic boosted flood mapping from satellite data, International Journal of Remote Sensing, 37, 993 – 1015, doi:/10.1080/01431161:2016:1145366, 2016.**

# Monitoring small reservoirs storage from satellite remote sensing in inaccessible areas

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**Abstract.** In river basins with water storage facilities, the availability of regularly-updated information on reservoir level and capacity is of paramount importance for the effective management of those systems. Yet, for the vast majority of reservoirs around the world, storage levels are either not measured or not readily available due to financial, political or legal considerations. This paper proposes a novel approach using Landsat imagery and Digital Elevation Models (DEM) to retrieve information on storage variations in inaccessible regions any inaccessible region. Unlike existing approaches, the method does not require any *in situ* measurement and is appropriate to monitor small, and often undocumented, irrigation reservoirs. It consists of three recovery steps: (i) a 2D dynamic classification of Landsat spectral bands information to quantify the surface area of water, (ii) a statistical correction of DEM data to characterise the topography of each reservoir and (iii) a 3D reconstruction algorithm to correct for clouds and Landsat 7 Scan Line Corrector failure. The method is applied to quantify reservoir storage in the Yarmouk basin in Southern Syria, where ground monitoring is impeded by the ongoing civil war. It is validated against available *in situ* measurements in neighbouring Jordanian reservoirs. Coefficients of determination range from 0.69 to 0.84, and the average relative error from 3 normalised root-mean-square error from 10 % to 3516 % for storage estimations on six Jordanian reservoirs with maximal water surface areas ranging from 0.59 km<sup>2</sup> to 3.79 km<sup>2</sup>.

## 1 Introduction

Reservoirs are essential for the development and management of a river basin's water resources, no matter their size (Liebe et al., 2005; Leemhuis et al., 2009). By increasing the availability of water during low-flow periods (International Commission On Large Dams, 2016), dams often play a key role in water supply, irrigated agriculture, hydropower generation, navigation, cattle breeding, fisheries, etc.

Despite these valuable applications, there is a scarcity of monitoring data as many countries cannot financially afford to build gauging stations (Solander et al., 2016). And even when monitoring systems do exist, there may not be institutions to collect the data, or legal means to disseminate it as it is often considered sensitive data (Alsdorf et al., 2007; Dombrowsky, 2007; Duan and Bastiaanssen, 2013). Yet this information is essential to conduct hydrological studies in committed basins, from defining

reservoir operation rules in simulation models (Yoon and Beighley, 2015), to assessing the impact of multi-reservoir systems on downstream river discharge (Vörösmarty et al., 1997; Hanasaki et al., 2006; Döll et al., 2009).

In that context, remote sensing is a promising tool to overcome the difficulty to access reliable information on a reservoir. This technique has also been applied to characterise a range of continental water bodies such as large lakes (Birkett, 1995; Ponchaut and Cazenave, 1998; Mercier et al., 2002), paddy rice fields (Islam et al., 2010) or tidal floods (Yan et al., 2010). The general procedure to monitor storage consists in associating water surface elevation and area after evaluating them independently (e.g., Frappart et al., 2006).

Satellite radar and laser altimetry are the predominant approaches to estimate the elevation of open water bodies (e.g., Morris and Gill, 1994; Crétaux and Birkett, 2006; Calmant et al., 2008; Gao et al., 2012; Wang et al., 2013), or their bathymetry (Arsen et al., 2014). Orbit repeat periods of radar altimeters such as Topex/Poseidon (T/P), GFO, Jason-1 and 2 or Envisat, range from 10 to 35 days. They have a high vertical accuracy with root-mean-square errors on the order of centimetres to tens of centimetres depending on the altimeter and the size of the water body (Calmant et al., 2008; Zhang et al., 2014)(Calmant et al., 2008; Crétaux et al., 2016). Yet, these the above mentioned sensors are affected by important drawbacks, including nadir viewing, narrow swath, coarse cross-track spacing (a few hundred kilometres), long along-track path length (about 1 km), large elevation differences around some water areas, that impede their application to more than a few hundred large lakes and reservoirs on the planet (i.e. area > 100 km<sup>2</sup> and width > 500 m) (Crétaux and Birkett, 2006; Alsdorf et al., 2007; Gao et al., 2012). More recent satellites such as Cryostat-2 or Sentinel-3 present significant improvements in terms of along-track resolution (~300 m). However, their respective inter-track of 7 km and 52 km (Donlon et al., 2012; Crétaux et al., 2016) still place many reservoirs out of the trajectory of their nadir-viewing sensors onboard. The small inter-track of Cryosat is also realised at the expense of a long revisit cycle (369 days) that impedes any monitoring of small reservoirs on a monthly basis. Alternatively, the Geoscience Laser Altimeter System onboard the Ice, Cloud, and Elevation Satellite (ICESat/GLAS) measured land surface elevations between 2003 and 2009 with a much finer spatial resolution (footprints' size between 50 and 105 m every 170 m along track), a vertical accuracy close to 10 cm (Zhang et al., 2011; Duan and Bastiaanssen, 2013), and a finer cross-track resolution (15 km maximum at equator (Zwally et al., 2002)). There was however no continuous elevation retrieving: ICESat/GLAS gathered data only during designated campaigns, with a long ground-track repeat cycle for almost all of it (183 days). Furthermore, unlike radar altimeters that can be used under all weather conditions (Birkett and Beckley, 2010), laser measurements are affected by the presence of thin clouds (Duan and Bastiaanssen, 2013). Many existing studies consequently used ICESat/GLAS data to get a trend on pre-determined large lakes variations over several years (e.g., Zhang et al., 2011; Duan and Bastiaanssen, 2013; Song et al., 2013), or to calibrate area-elevation relationships for a limited number of water bodies large enough for the satellite to take sufficient elevation measurements per track (Zhang et al., 2014).

Water surface areas are commonly determined from optical satellite imagery such as MODerate Resolution Imaging Spectroradiometer (MODIS) and Landsat products (Xiao et al., 2006; Gao et al., 2012), or Synthetic Aperture Radar (SAR) sensors (e.g., RADARSAT, JERS-1 or ERS ) (Annor et al., 2009; Duan and Bastiaanssen, 2013), ERS or Sentinel-1) (Annor et al., 2009; Duan and Bastiaanssen, 2013; Amitrano et al., 2014). The latter has however been less used due to the difficulty to get consistent results, as the required condition of a significantly lower phase coherence of water areas than of the surrounding land surface

is not always met with orbital repeat cycles of more than a few days, or with wind or rain (Alsdorf et al., 2007; Eilander et al., 2014). Therefore, existing approaches have used either MODIS or Landsat depending on their emphasis on spatial or temporal resolution (Solander et al., 2016; Zhang et al., 2016). Images acquired during the various Landsat missions have a much finer spatial resolution (30 m) than MODIS's (250 m for the red band, 500 m for infrared), but they are taken on a repeat cycle of 16 days compared to the daily MODIS products. The higher revisit frequency of MODIS satellites allows MODIS-based approaches to better address clouds and smoke artifacts on optical images. However MODIS missions cover a much shorter period (July 2000 to present) than Landsat missions (July 1982 to present). [The potential of the recent two Sentinel-2 satellites can also be mentioned for post-2015 studies. Launched in June 2015 \(Sentinel-2A\) and March 2017 \(Sentinel-2B\), they provide spectral bands at a resolution of 10 m for visible and NIR bands, and at 20 m for SWIR bands. They also have a repeat cycle of 5 days by combining the two \(European Space Agency, 2013; Yang et al., 2017\).](#)

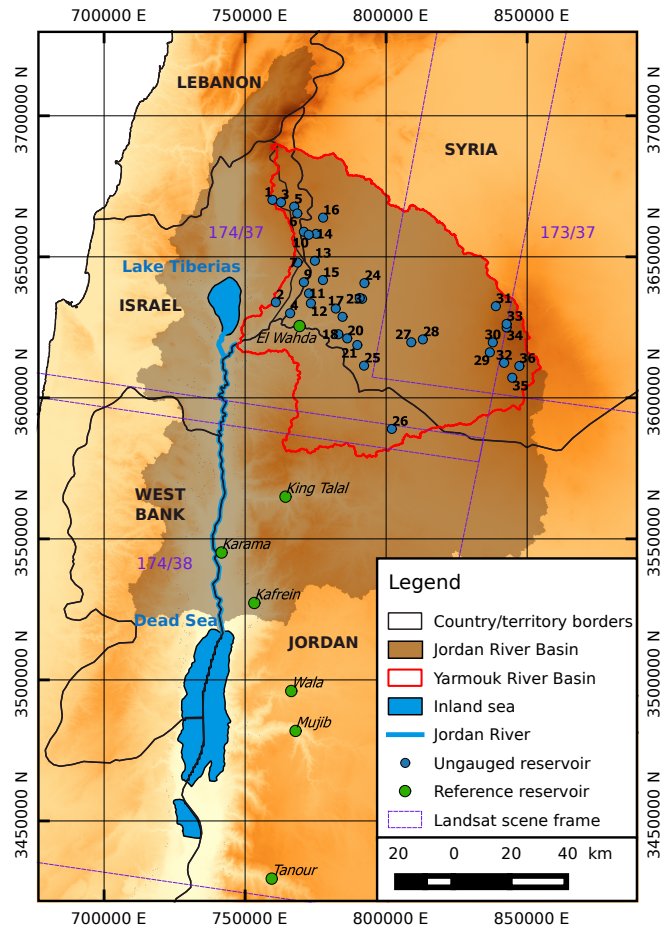
The common protocol to separate water areas from other land use categories is to apply a threshold to indices such as the Normalised Difference Vegetation Index (NDVI) (e.g., Frappart et al., 2006; Gao et al., 2012), or the Modified Normalised Difference Water Index (MNDWI) proposed by Xu (2006) (e.g., Crétaux et al., 2015; Müller et al., 2016). But determining an adequate value for a multi-temporal analysis can be challenging because such a threshold is known to be case-dependent (Liu et al., 2012)(Liu et al., 2012; Coltin et al., 2016). Furthermore, separating water from land or vegetation may be difficult due to subpixel land-cover components (Ji et al., 2009), or water quality that can vary throughout a water body (Gao et al., 2012). To address these issues, decision tree defined thresholds have successfully been applied with various vegetation indices (e.g., Xiao et al., 2006; Islam et al., 2010; Yan et al., 2010), but remain case-dependent. [Coltin et al. \(2016\) have then advocated the implementation of automatic thresholds as they developed a supervised learning approach to improve flood mapping.](#)

Other methods like unsupervised classification (Wang et al., 2008), or direct elevation-area relationship from Digital Elevation Model (DEM, Wang et al., 2005) have also been tested but did not prove to be more precise. Gao et al. (2012) recently developed a method to combine both an index analysis and an unsupervised classification to improve the accuracy of the delineation of water areas. The approach was refined by Zhang et al. (2014) who enhanced the storage assessment with a novel surface area retrieval algorithm.

While promising, these approaches generally fail to systematically combine remote sensing surface area and elevation due to the different timing in orbital repeat cycles of different satellites. Elevation-area relationships are then deduced from remote sensing data that is available at the same time (e.g., through linear or polynomial regressions, Gao et al., 2012; Duan and Bastiaanssen, 2013; Song et al., 2013), so that reservoir storage can be computed with either remote sensing elevation or area only. Even then, existing methods estimate storage in relative terms, either from the already known elevation, area and storage at capacity (Zhang et al., 2014), or from the lowest water level detected (Duan and Bastiaanssen, 2013).

Furthermore, these approaches have only been applied to reservoirs larger than 100 km<sup>2</sup>, which are estimated to represent only 0.54 % of reservoirs larger than 0.1 km<sup>2</sup> in the world (Lehner et al., 2011). Studies that analysed small reservoirs delineated water surface with Landsat optical sensors (e.g., Liebe et al., 2005; Sawunyama et al., 2006; Rodrigues et al., 2012) or radar images to address the cloud cover issue (Annor et al., 2009; Liebe et al., 2009), and could only get an estimation of storage



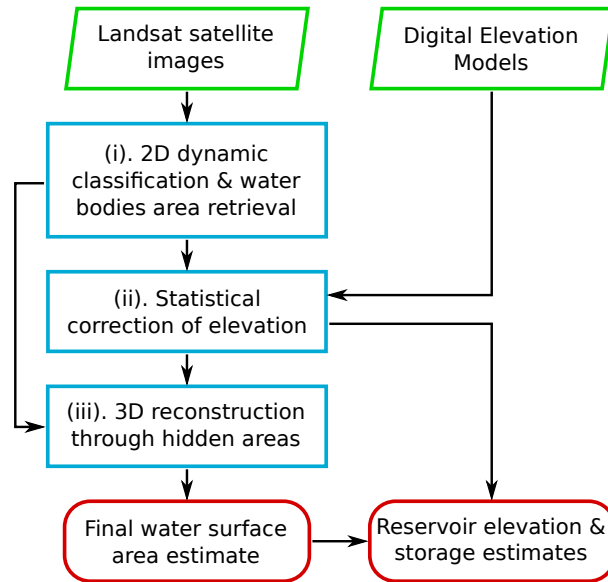


**Figure 1.** Reservoirs identified in Jordan and the Yarmouk River Basin using the method developed in this paper. Because *in situ* measurements are accessible for those managed by Jordan, they are used to validate the method. All coordinates are expressed in the Coordinate Reference System (CRS) WGS 84 / UTM zone 36N (EPSG:32636), in which 1 unit equals 1 m.

capacities by conducting bathymetrical surveys. Due to their reliance on *in situ* observations, these methods are inapplicable to remote, ungauged or conflict-prone areas.

This paper introduces a new method to monitor reservoir storage based on remote sensing data exclusively. The method is applied to small reservoirs – capacities and water surface areas starting from 1 hm<sup>3</sup> (million cubic metre) and 0.5 km<sup>2</sup> respectively – in the Yarmouk River Basin (YRB, see Fig. 1) in Southern Syria during the ongoing civil war and the decade before it started. Its prediction performance is tested against available *in situ* observations of reservoir storage and elevation in neighbouring Jordan.

The document is organised as follows: Sect. 2 presents the method and algorithms developed for the monitoring of reservoir storage, Sect. 3 reviews results, error measurements and sensitivity analysis, and Sect. 4 concludes the study.



**Figure 2.** Flowchart of the whole procedure.

## 2 Methodology

The procedure is based on two types of data: Landsat images for water areas estimation, and DEM for topography. It works in three stages that are presented in the flowchart on Fig. 2. The idea behind the process is (i) to use Landsat bands to enhance the detection of water pixels, then (ii) to exploit this information to statistically correct the DEM vertical errors and characterise reservoir bathymetry, and (iii) to use the updated topography to reconstruct missing parts of Landsat images (e.g., pixels covered by clouds or not captured by the Landsat sensor).

### 2.1 2D dynamic classification and water bodies area retrieval

Landsat images are chosen because they are freely available with a spatial resolution fine enough (30 m) to detect variations in the area of small reservoirs. The spatial resolution of MODIS images is indeed too coarse to assign to any small reservoir a proper range of area and elevation (1 km<sup>2</sup> is covered by 16 MODIS image 250 m pixels only). Thus, about 300 Landsat 4, 5, 7 and 8 images for each scene – index 173/37 above a part of the YRB, 174/38 above reservoirs in Jordan, and 174/37 above parts of both in the Worldwide Reference System (WRS, see the scene frames in Fig. 1) – are downloaded from the United States Geological Survey (USGS) EarthExplorer website (<https://earthexplorer.usgs.gov/>).

#### 2.1.1 Fmask

We use the Fmask (Function of mask) algorithm (Zhu and Woodcock, 2012; Zhu et al., 2015) to discriminate cloud coverage from open water. The algorithm was originally designed to separate potential cloud pixels from clear sky pixels on Landsat

images using empirical thresholds on NDVI and the near-infrared band, with an overall accuracy of 96.41 % (Zhu and Woodcock, 2012). Fmask distinguishes land and water areas and produces a probability mask for clouds, which we use to manually remove images that are almost entirely covered by clouds or with obvious large errors in water bodies detection. After quality control, about 245 images remain per location.

5 Most pixels classified as water by Fmask can reasonably be considered as water due to the relatively selective thresholds used in the algorithm. Hence, at this stage, the uncertainty remains with regard to pixels hidden by clouds or cloud shadows, misclassified by Fmask as land or snow, or not captured by the Landsat sensor (e.g., “N/A” stripes caused by the Landsat 7 Scan Line Corrector (SLC) failure, see Fig. 4 (a) and (b)). Our analysis reveals that, on average, 24.1 % of reservoirs’ pixels are misclassified as land, 8.1 % are covered with clouds or cloud shadows, and 8.6 % are in “N/A” areas (see Sect. 3.1).

### 10 2.1.2 Occurrence mask

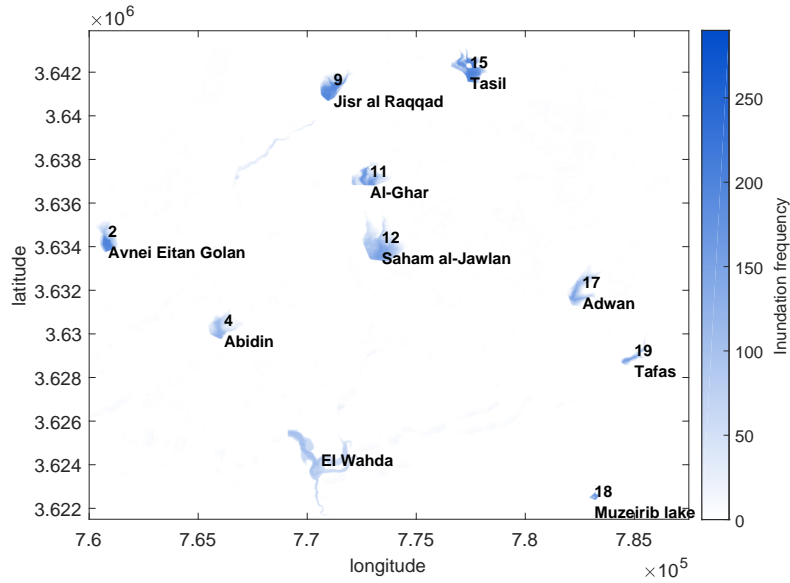
We use the frequency with which pixels are classified as water to distinguish actual reservoirs from small pools or misclassified land, and to delimit them. For each Landsat scene, the ~245 satellite images are superimposed to form an image where each pixel represents the number of times it has been covered by water (see Fig. 3). This occurrence mask ( $\mathbf{M}_{\text{occ}}$ ) is useful to filter occasional Fmask’s classification errors, and to create a water mask ( $\mathbf{M}_{\text{wat}}$ ): pixels with values greater than 5 in  $\mathbf{M}_{\text{occ}}$  are classified as water and kept in  $\mathbf{M}_{\text{wat}}$ , while those with lower values are considered as misclassified land and removed from water bodies (i.e. hidden by  $\mathbf{M}_{\text{wat}}$ ). In practice, the threshold of 5 was empirically chosen after comparing detected water bodies with Google Earth high resolution (~1 m) imagery. The same threshold was is applied to reservoirs located in the overlapping area of two Landsat images as it did does not change their contours. Its small value is justified by the fact that most images with obvious mistakes have already been manually discarded at the previous step.

20 Aside from sporadic large wadis (intermittent rivers) that are manually removed from the mask, final water bodies in  $\mathbf{M}_{\text{wat}}$  are deemed to be reservoirs. They are the ones depicted in blue and green dots on the map in Fig. 1.

### 2.1.3 Classification enhancement for each Landsat image

The detection of water bodies is enhanced using NDVI and MNDWI rasters computed from Landsat imagery. A low NDVI can be attributed to both water and bare land, and a low MNDWI value can denote either water or clouds. We combine these indices and leverage their complementary nature to detect open water.

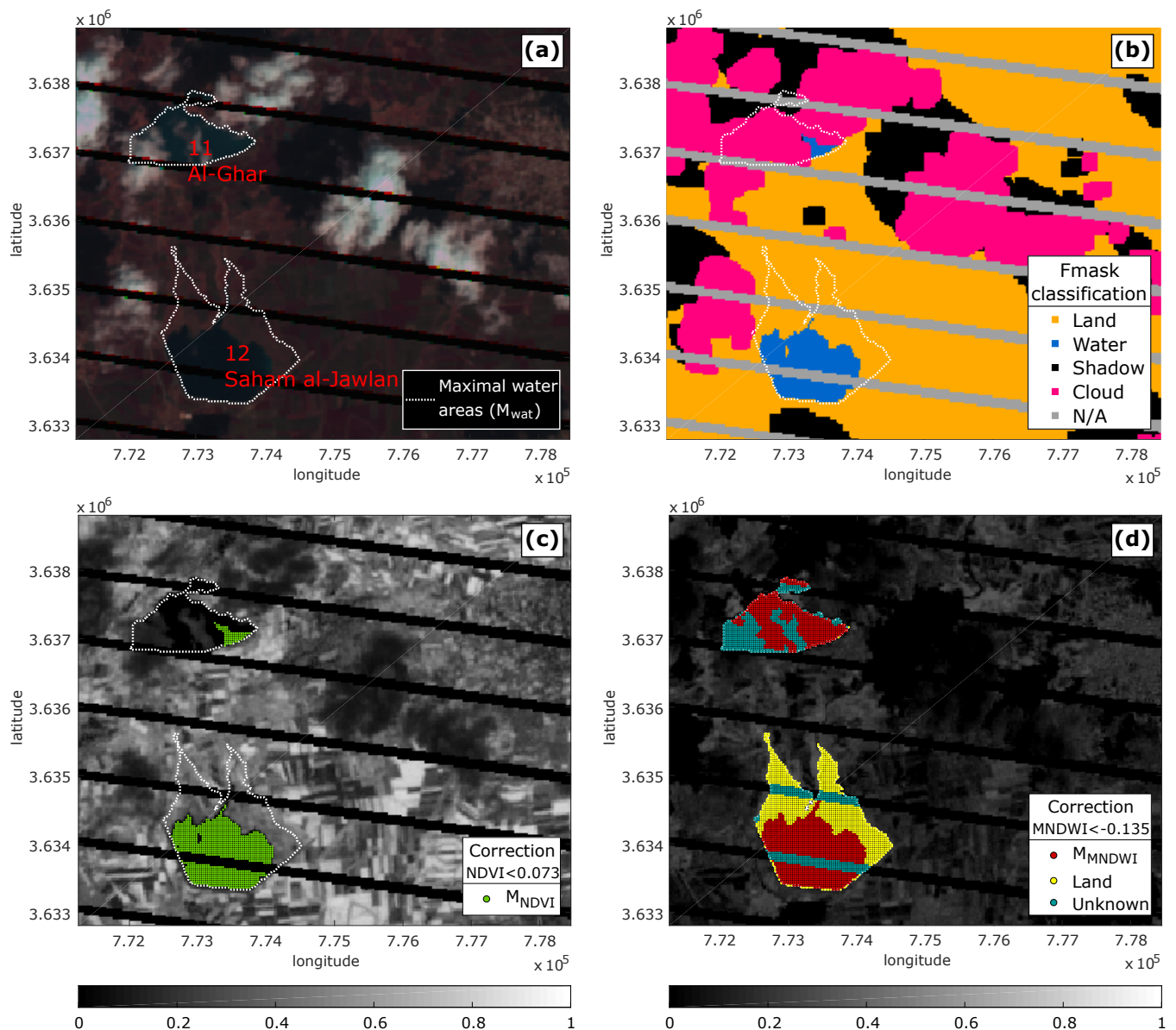
To ensure more reliable and repeatable values for identical land use categories in different images, the two indices are computed from Top of Atmosphere (TOA) reflectance to which surface reflectance, which is estimated by applying the imaged-based atmospheric correction Dark Object Subtraction 1 (DOS1, Chavez, 1996) has been applied to estimate surface to Top of Atmosphere (TOA) reflectance. However the DOS1 adjustment is not optimal because not based on actual atmospheric or cloud cover measurements. Moreover, the slight band variations between the various Landsat missions may affect NDVI and MNDWI, and may require different thresholds to detect water. Consequently, two supplementary water detection adjustments are performed through the method presented in the flowchart on Fig. 5 to define a MNDWI threshold adapted to each date and climatic



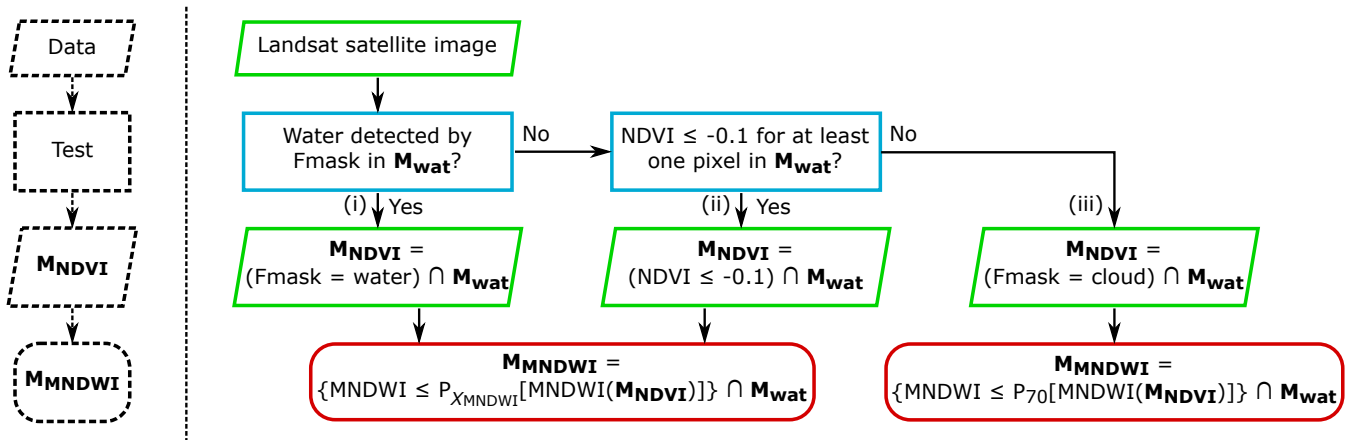
**Figure 3.** Image of the number of times each pixel has been covered by water ( $M_{occ}$ ). Text in black indicates the identification number (for Syrian reservoirs) and name of known reservoirs. Coordinates are expressed in CRS WGS 84 / UTM zone 36N, in which 1 unit equals 1 m.

conditions (i.e. each time  $t$  over a given scene). A NDVI mask ( $M_{NDVI}(t)$ ) is first created to calibrate the MNDWI threshold, which is then used to build a MNDWI mask representing water areas ( $M_{MNDWI}(t)$ ):

1. The goal of  $M_{NDVI}(t)$  is to find with NDVI all pixels where there could potentially be water. Depending on the results of the Fmask classification in  $M_{wat}$ , three situations can arise:
  - 5 (i) If water is already detected by Fmask in  $M_{wat}$  reservoirs,  $M_{NDVI}(t)$  is formed from those ones (see green dots in the Fig. 4 (c) example).
  - (ii) Where water is not detected by Fmask, we impose a threshold on the NDVI. Pixels with a NDVI lesser than  $-0.1$  in  $M_{wat}$  are used to form  $M_{NDVI}(t)$ . The lowest values are indeed generally typical of water. This condition has been added to take into account images where thin clouds cover reservoirs.
  - 10 (iii) In  $\sim 1\%$  of all images, no pixel meets the previous conditions, even if water can be seen by eye on the original spectral bands. We have indeed noticed that for these few cases, Fmask associates water bodies to clouds.  $M_{NDVI}(t)$  is thus built on pixels classified as cloud in  $M_{wat}$ .
2. The detection of water bodies is further enhanced by imposing a threshold on MNDWI images. The threshold is defined automatically so as to optimally distinguish water bodies from clouds. For the two first situations, the threshold is set to
  - 15 the  $X_{MNDWI}^{th}$  percentile ( $P_{X_{MNDWI}}$ ) of MNDWI values in  $M_{NDVI}(t)$ .  $X_{MNDWI}$  is set to the maximum, 100, in order to avoid over-constraining the classification. The sensitivity of the method to the choice of this parameter is presented in Sect. 3.2 further below. For the third case, the threshold is set to the 70<sup>th</sup> percentile ( $P_{70}$ ) of MNDWI values in  $M_{NDVI}(t)$ .



**Figure 4.** 2D dynamic water classification over a part of a Landsat 7 image (174/37) obtained on March 30<sup>th</sup>, 2010. [Coordinates are expressed in CRS WGS 84 / UTM zone 36N, in which 1 unit equals 1 m.](#) (a) SWIR-R-G image. Two reservoirs can be seen by eye – even if their appearance is very similar to cloud shadow areas –, but the hedges are not easy to detect due to the cloud cover. (b) Results of the Fmask classification. Water areas detection is not precise enough to directly use the results for the estimation of reservoirs surface area. (c) NDVI image. Water pixels’ low NDVI here contrasts with the surrounding irrigated crops’ high NDVI, as the two reservoirs are located close to cultivation areas. (d) MNDWI image. Red dots indicate water areas obtained after the 2D enhancement (Sect. 2.1). The 3D reconstruction is operated later (Sect. 2.3) on the *Unknown* part.



**Figure 5.** 2D dynamic classification procedure.

Finally, the water mask – or MNDWI mask –  $\mathbf{M}_{\text{MNDWI}}(t)$  is formed by including only areas with a MNDWI lesser than the MNDWI threshold in  $\mathbf{M}_{\text{wat}}$ . This last step allows to incorporate most water pixels left out by Fmask and undetectable with NDVI (see red dots in Fig. 4 (d)).

After removing water areas smaller than 20 pixels ( $20 \times 900 \text{ m}^2$ ), considered noise, the classified images have three categories: (i) *Water* as identified by the protocol developed above, (ii) *Land* according to Fmask, and if not in the category *Water*, and (iii) *Unknown* that include all other pixels (see Fig. 4 (d)).

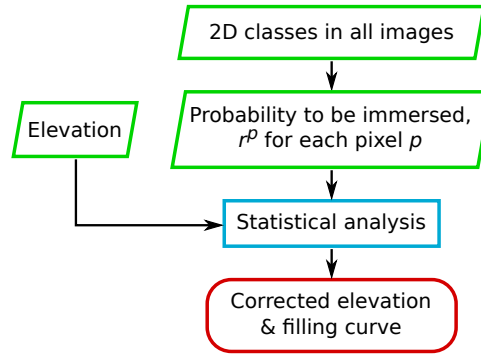
## 2.2 Statistical correction of elevation

### 2.2.1 Digital elevation models

Unlike most studies, the proposed method does not rely on satellite altimetry to assess water bodies' elevation, but on DEMs to get the topography. It is then required that reservoirs were almost empty or not yet built when the DEM satellites passed over them, for at least one of the two sources considered: ASTER GDEM v2 and SRTM-C/X. ASTER GDEM v2 data was acquired between 2001 and 2008, and SRTM-C/X data on February 11–22, 2000. All have a spatial resolution of 1" (approximately 30 m at the equator), which we resample to match Landsat images. The large coverage of these datasets is chosen over the very low precision of the measures. They indeed cover almost all Earth's land surface (except for SRTM-X): from  $83^\circ \text{ N}$  to  $83^\circ \text{ S}$  for ASTER GDEM v2, and from  $60^\circ \text{ N}$  to  $56^\circ \text{ S}$  for SRTM-C; but the vertical relative precision is very low compared to satellite altimetry: objectives of 15 m and 6 m for 90 % of SRTM-C and SRTM-X data respectively (German Aerospace Center (DLR), 2017; Rodriguez et al., 2005), and standard deviations estimated to 3.95 m and 8.68 m for SRTM-C and ASTER data respectively (ASTER GDEM Validation Team, 2011).

## 2.2.2 Elevation-area relationship

To improve elevation assessment, DEMs are statistically corrected by using the information on water surface areas obtained from Landsat images. The protocol presented in Fig. 6 is implemented for each reservoir:



**Figure 6.** Procedure for the statistical correction of topography.

1. A water coverage quantile is computed at each pixel to determine the probability for it to be immersed. To each pixel  $p$  is associated the ratio  $r^p$  defined as:

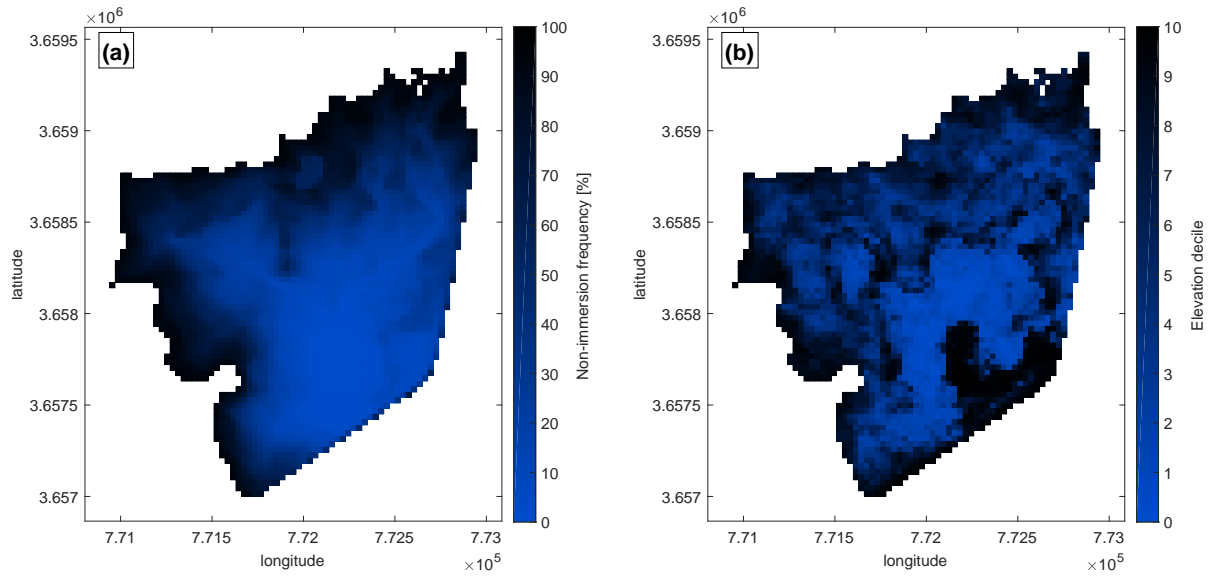
$$r^p = \frac{N_{water}^p}{N_{water}^p + N_{land}^p} \quad (1)$$

where  $N_{water}^p$  is the number of times the given pixel  $p$  is counted as Water, and  $N_{land}^p$  the number of times it is counted as Land. We ignore the images where the pixel  $p$  is classified as Unknown.

2. Each To illustrate the interest of this section, Figure 7 shows both  $r^p$  and the relative elevation in the Kudnah reservoir.

We can see that the two do not always match as we would expect – i.e. lowest pixels are not always the most frequently immersed, nor are the highest pixels the most rarely immersed. The immersion frequency ( $r^p$ ) can actually be used to correct the elevation. The former, which is estimated from the results of the 2D classification enhancement, is indeed assumed more reliable than the original DEM. Hence, each pixel's elevation  $H^p$  is put in relation with the area  $A^p$ , defined as the cumulated area of all pixels  $q$  for which  $r^q \geq r^p$  in the reservoir for which  $r^q \geq r^p$ .

The examples of Fig. 7 suggest that pixels' elevation is 8 confirm the observations made on Fig. 7: pixels' elevations are not always correlated with the number of times they are classified as water. To a certain extent this the difference was expected from the DEM's low vertical precision, but some “anomalies” concerning the most often immersed pixels (i.e. lowest  $A^p$ ) can be recurrent from one reservoir to another due to either a strong dispersion in elevation (see SRTM-X data in Fig. 7 8 (b)), or a flat elevation (see SRTM-C data in Fig. 7 8 (c)). We interpret this irregularity as arising from the presence of water where the satellite tried to evaluate elevation: in the case of SRTM-X, the measure over water is



**Figure 7.** (a) Relative non-immersion frequency ( $1 - r^p$ , from the 2D classes) and (b) elevation (from the DEMs, in terms of decile) in the Kudnah reservoir. Coordinates are expressed in CRS WGS 84 / UTM zone 36N, in which 1 unit equals 1 m.

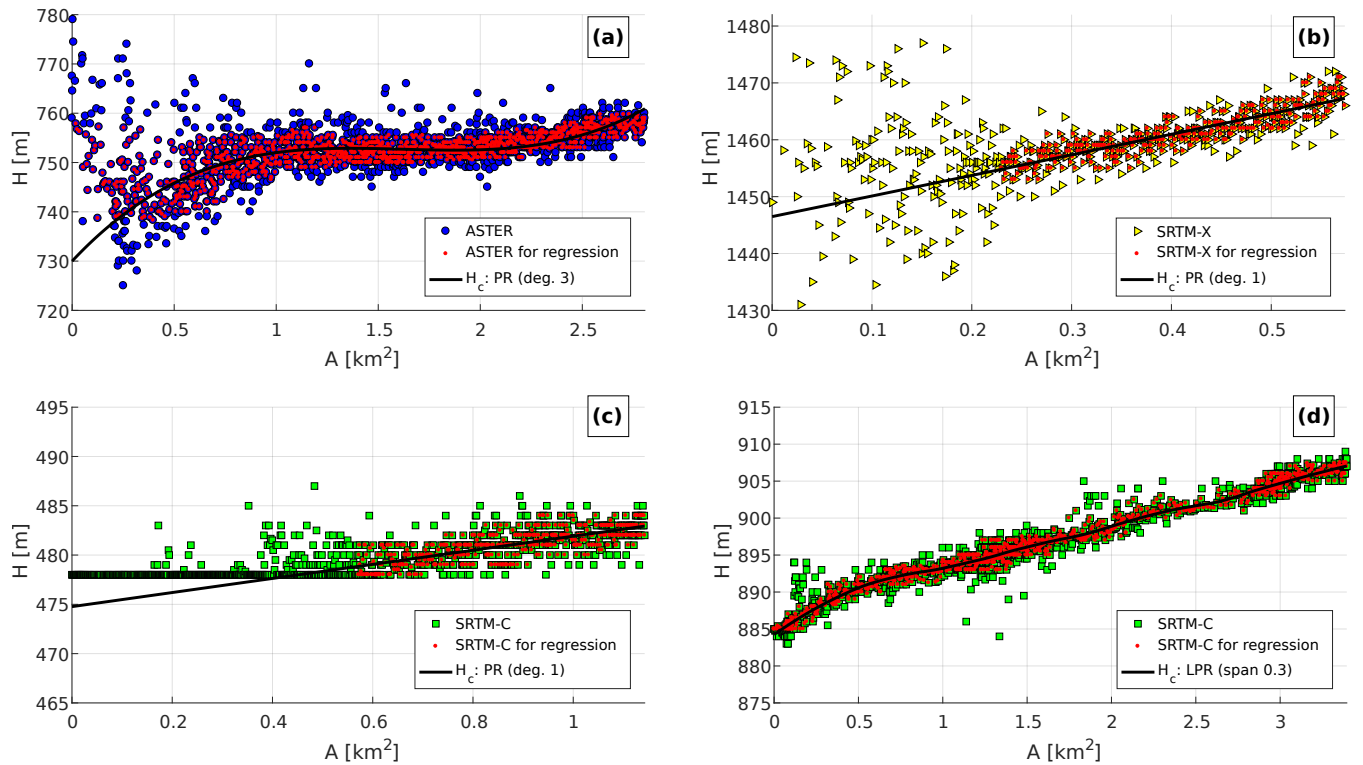
hampered for reasons inherent to the use of a SAR sensor; and in the case of SRTM-C, DEM pixels covered with water may have been filled during a post-treatment analysis. Either way, elevation cannot be retrieved from the given DEM for these reservoirs’ most often immersed pixels.

3. To address the issue, a polynomial regression on observed land pixels ( $A > A_i$ , with  $A_i$  the area assumed as immersed during the satellite elevation retrieval) is used to build a “corrected elevation”-area relationship ( $A \rightarrow H_c(A)$ ) that smoothes the data and filters potential errors. Extreme values best fits the data (on a least-squares sense). Values of  $H$  are ignored greater than the 80<sup>th</sup> or lower than the 20<sup>th</sup> percentile are ignored to filter potential errors and smooth the data. This step is executed three times – one for each DEM – and the better quality dataset (i.e., the one with less dispersion and fewer “anomalies” as defined above) is kept. A few examples Examples are shown in Fig. 78.
4. A filling curve – volume-area relationship – is finally constructed using the outcomes of the previous step.

The regression relies on the assumption that elevation estimates are correct on average by considering many pixels. Indeed, the relative error on elevation approaches zero when the number of images taken into account grows. This property has already been used by LeFavour and Alsdorf (2005) for instance, in order to estimate the slope of the Amazon River.

Parameters and results of the regression for reservoirs that fulfil the criteria mentioned at the beginning of this article – maximum storage and area larger than  $1 \text{ hm}^3$  and  $0.5 \text{ km}^2$  respectively – are summarised in Table 1.





**Figure 8.** Elevation-area relationship and regression for a few reservoirs in the Yarmouk River Basin: (a) Kudnah, (b) Roum, (c) Al Ghar and (d) Qunaitera. Each symbol (circle, square or triangle depending on the DEM) represents the information associated to one pixel in a reservoir. *PR* and *LPR* stand for Polynomial Regression and Local Polynomial Regression respectively.

### 2.3 3D reconstruction through hidden areas

Retrieving missing parts of water bodies in the Unknown areas means dealing with Landsat drawbacks: (i) the 16 days repeat cycle making images regularly covered by clouds, and (ii) the failure of the Landsat 7 SLC that led to large data losses for the Enhanced Thematic Mapper Plus (ETM+) sensor after May 2003 (see grey stripes in Fig. 4 (b)).

- 5 Zhang et al. (2014) developed an approach to improve quite significantly the estimation of reservoir's water area. However, their method requires that only a small part of the reservoir is misclassified or hidden. This is not a problem if one works with MODIS images over very large reservoirs, but in our situation – Landsat images over small water bodies – the condition is rarely met.

We developed an alternate algorithm to use the information from each individual pixel:

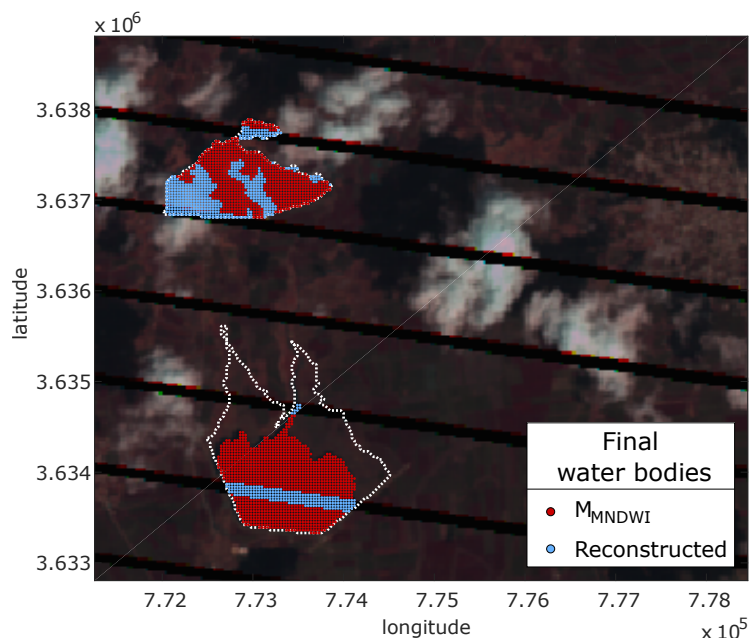
- 10 1. As the area  $A^p$  has been associated to each pixel  $p$ , and  $H_c$  has been expressed in terms of  $A$ , a corrected elevation is associated to each pixel in a reservoir.

Location	Reservoir	DEM	Visible area $1 - \frac{A_i}{A_{\max}} [\%]$	Regression	$R^2$	$A_{\max}$ [km <sup>2</sup> ]	$\Delta H_{c\max}$ [m]	$V_{\max}$ [hm <sup>3</sup> ]
Israel-controlled	Al Manzarah	ASTER	100	PR (deg. 2)	0.34	0.53	9.14	2.64
Golan Heights	Avnei Eitan Golan	ASTER	70	PR (deg. 2)	0.31	0.93	4.88	2.34
Syria	Abidin	ASTER	65	PR (deg. 1)	0.37	1.16	8.74	5.07
	Qunaitera	SRTM-C	100	LPR (span 0.3)	0.98	3.40	22.81	33.94
	Jisr al Raqqad	ASTER	30	PR (deg. 1)	0.52	1.16	16.23	9.43
	Kudnah	ASTER	100	PR (deg. 3)	0.46	2.81	30.92	29.45
	Al Ghar	SRTM-C	50	PR (deg. 1)	0.56	1.14	8.17	4.66
	Saham al-Jawlan	SRTM-C	55	PR (deg. 1)	0.84	2.48	12.93	15.99
	Ghadir al-Bustan	ASTER	50	PR (deg. 1)	0.56	1.19	15.02	8.93
	Tasil	ASTER	60	PR (deg. 1)	0.28	1.28	9.59	6.15
	Adwan	ASTER	100	PR (deg. 1)	0.33	1.31	7.92	5.17
	Ebtaa kabeer	SRTM-C	80	PR (deg. 1)	0.71	0.73	6.56	2.39
	Sheikh Misikin	SRTM-C	45	PR (deg. 1)	0.71	2.85	7.51	10.71
	Roum	SRTM-X	60	PR (deg. 1)	0.81	0.57	20.77	5.94
	Sahwat al-Khadr	SRTM-C	80	PR (deg. 3)	0.78	1.27	10.07	6.49
Border Jordan-Syria	El Wahda	SRTM-C	100	LPR (span 0.3)	0.97	2.69	53.31	66.72
Jordan	Karama	SRTM-C	85	LPR (span 0.1)	0.90	3.79	17.00	35.91
	Kafrein	SRTM-C	30	PR (deg. 1)	0.56	0.66	17.80	5.85
	Tanour	SRTM-C	85	PR (deg. 1)	0.94	0.59	36.00	10.56
	King Talal	SRTM-C	20	PR (deg. 1)	0.29	2.17	31.66	33.69
	Wala	SRTM-C	100	LPR (span 0.5)	0.85	0.61	25.86	6.37
	Mujib	SRTM-C	50	LPR (span 0.3)	0.79	1.30	44.33	30.49

**Table 1.** Parameters and results of the elevation-area regression. *PR* and *LPR* stand for Polynomial Regression and Local Polynomial Regression respectively.  $R^2$  is the coefficient of determination between the corrected elevation  $H_c$  and the elevation  $H$  for pixels taken into account by the regression (red dots in Fig. 78).

2. Each pixel in an Unknown area adjacent to water areas is set to Water if: (i) the pixel is in  $\mathbf{M}_{\text{wat}}$ , and (ii) its corrected elevation  $H_c^p$  is lesser than the  $X_{H_c}^{\text{th}}$  percentile of corrected elevation in all adjacent water bodies. This threshold is set to 98 to ignore highest values of  $H_c$ , in case they were associated to pixels misclassified as water. A sensitivity analysis has been conducted with regard to this threshold, and the results are available in Sect. 3.2 further below.
- 5 This water body reconstruction technique relies on the fact that a pixel that is often immersed likely has an elevation lower than a pixel that is rarely immersed. This is a reasonable assumption due to the large number of images analysed. Blue dots in Fig. 8

9 show how the 3D reconstruction complements the previous 2D information retrieval. Finally, storage variations are obtained by combining final reconstructed areas with the previously determined filling curves.



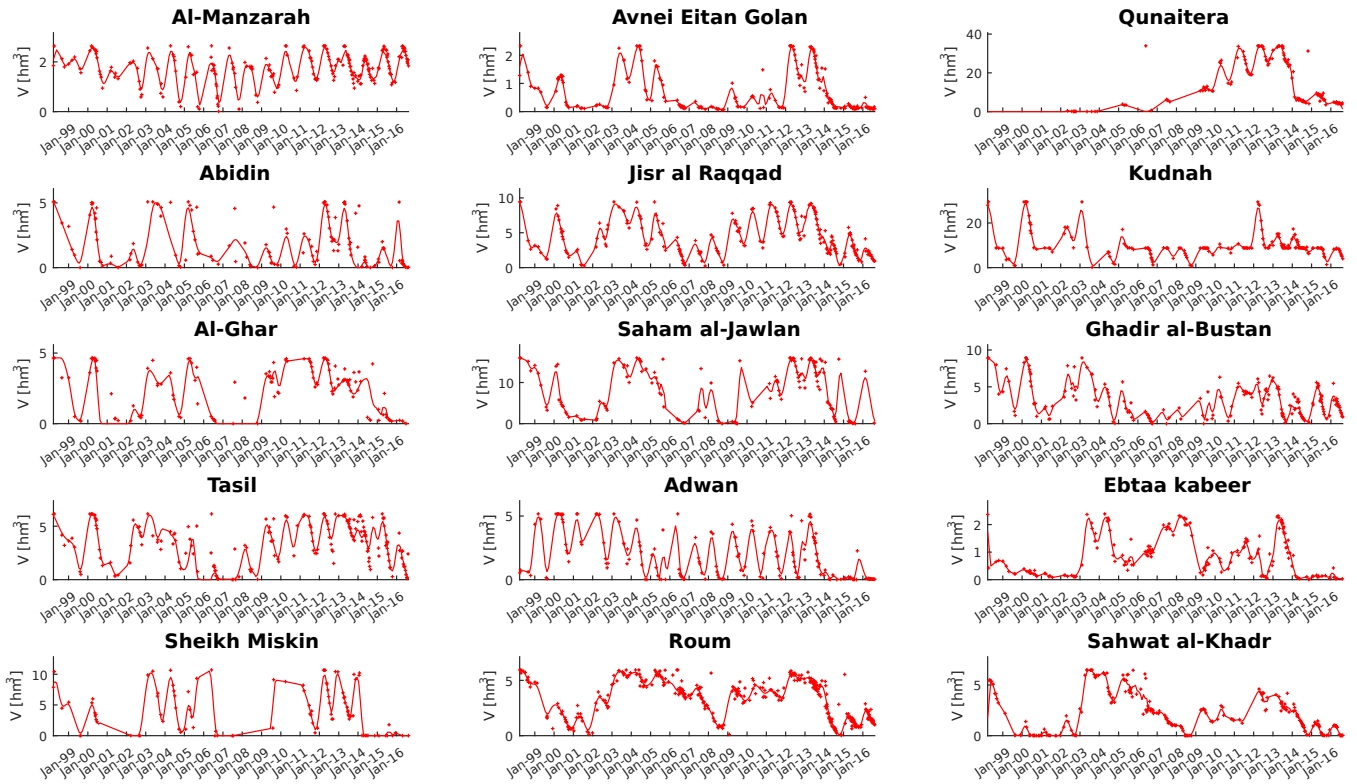
**Figure 9.** SWIR-R-G image. Final water bodies as obtained after the 2D enhancement and the 3D reconstruction applied to the Landsat 7 image (174/37) taken on March 30<sup>th</sup>, 2010 (same as Fig. 4). Coordinates are expressed in CRS WGS 84 / UTM zone 36N, in which 1 unit equals 1 m.

### 3 Results

#### 3.1 Storage variations: validation and discussion

- 5 Storage variations estimated by remote sensing for all reservoirs that cannot be gauged in the YRB are displayed in Fig. 910. These reservoirs are located in Syria and in the Israel-controlled Golan Heights. We can see By qualitatively comparing our results to those obtained by Müller et al. (2016) (monitoring of Syrian reservoirs using Landsat 7 datasets but before the 2D and 3D corrections), we can see more coherent storage variations through the presence of annual drawdown-refill cycles, which – particularly for Roum and Sahwat al-Khadr. It means that the 2D enhancement and 3D reconstruction steps have improved
- 10 the detection of water and helped to overcome the low Landsat repeat cycle of 16 days.

Reservoirs managed by Jordan are used to validate the method by comparing our remote sensing estimates of elevation and storage with monthly *in situ* measurements conducted by the Jordan Valley Authority (JVA). With the exception of the King Talal dam, our results seem to follow quite accurately the historical records (see Fig. 10). 11). For some reservoirs (i.e., Karama and Tanour), the method seems to have difficulties to predict highest storages. Indeed, if the number of high-elevation

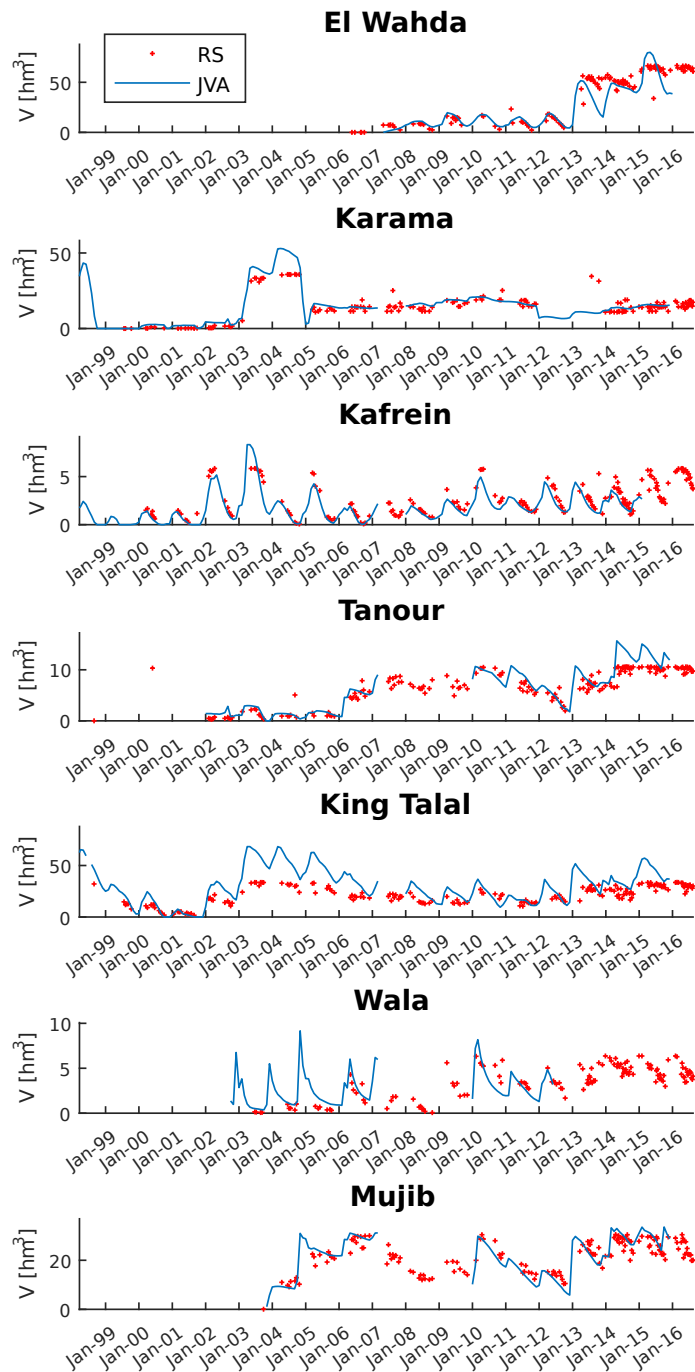


**Figure 10.** Storage variations. Red crosses indicate estimates from the method developed in this paper. Red lines are local polynomial regressions, that are plotted only with the purpose of showing storage variation trends.

pixels is small, the uncertainty on their corrected elevation (and thus the filling curve) can potentially affect the estimate of the maximum storage. This may be a limitation of the method. In addition, we can note that elevation  $H$  and volume  $V$  may vary a lot from month to month: up to 10 m or 15  $\text{hm}^3$  – i.e. 50 % of the maximal storage – for instance for the Mujib reservoir. **Some** Because no information is available regarding the data collection date, some of the differences between our estimates and measured data might then come from **the inaccuracy regarding the data collection date** **this lack of metadata**.

With regard to the King Talal reservoir, we can see large errors in storage estimates (see Fig. 1011). But they could have been expected at the end of the elevation-area relationship establishment step: the assumptions that were made to define  $H_c$  were maybe not justified in this case. Indeed, 80 % of the reservoir maximal area was covered with water when the SRTM satellite passed over the dam, and the  $R^2$  is only 0.29 for the regression applied to the remaining visible pixels (see Table 1).

A small visible surface area does not necessarily lead to a low quality elevation-area relationship – see the good estimates for the Kafrein reservoir, while 70 % of its maximal area was hidden when the SRTM satellite passed over it –, but it certainly is a sign that results might be biased.



**Figure 11.** Storage variations for Jordan managed reservoirs. Red crosses indicate estimates from the method developed in this paper. The blue lines indicate *in situ* data records that were made by the Jordan Valley Authority (JVA).

Errors on the estimation of elevation and storage are evaluated in terms of the coefficient of determination ( $R^2$ , Eq. 2) and the average relative error ( $\epsilon_m$ , normalised root-mean-square error (NRMSE), Eq. 3):

$$R^2 = \frac{Cov(RS, Hist)^2}{\sigma_{RS}^2 \cdot \sigma_{Hist}^2} \quad (2)$$

$$\epsilon_m \text{NRMSE} = \frac{1}{N} \frac{1}{Hist_{\max} - Hist_{\min}} \sqrt{\sum_{i=1}^N \frac{(RS_i - Hist_i)^2}{N}} \quad (3)$$

where  $Cov(RS, Hist)$  is the covariance between remote sensing (RS) estimates and JVA historical measurements,  $\sigma^2$  the variance, and  $N$  the number of RS estimates during the period that in which JVA measured storage or elevation. Results are presented in Table 2.

Reservoir	N		R <sup>2</sup>		NRMSE			
	H <sub>c</sub>	V	H <sub>c</sub>	V	H <sub>c</sub>	V		
El Wahda	25	107	0.54	0.76	0.49	0.30	0.20	0.15
Karama	29	123	0.98	0.79	0.00	0.05	0.13	0.10
Kafrein	35	136	0.91	0.81	0.00	0.11	0.35	0.10
Tanour	16	117	0.83	0.84	0.09	0.12	0.12	0.15
King Talal	40	159	0.50	0.76	0.87	0.36	0.15	0.19
Wala	15	37	0.36	0.69	0.27	0.21	0.13	0.16
Mujib	15	104	0.73	0.75	0.18	0.15	0.03	0.15

**Table 2.** Errors in terms of  $R^2$  and average relative error NRMSE for Jordanian reservoirs'  $H_c$  and  $V$  assessments.

The coefficient of determination for storage ranges from 0.69 to 0.84. These high values confirm an important correlation and the similar variation trends that can be seen between the method's estimates and JVA records (see Fig. 1011). A few high  $|\epsilon_m|$  NRMSE values for both  $V$  and  $H_c$  though indicate that there is still some uncertainty with regard to the estimation of their absolute value at a given month. Indeed, by ignoring the King Talal dam,  $|\epsilon_m|$  ranges from 3 NRMSE ranges from 10 % to 3516 % for storage, and reaches up to 4930 % for elevation. These error estimates for elevation though need to be taken into account with caution due to the small number of JVA measurements available for comparison ( $15 \leq N \leq 35$ ).

In order to better evaluate the proposed method compared to a basic fixed NDVI and near-infrared thresholds water area detection, we consider the results presented in Table 3: on average, only 30.0 % to 59.4 % of final reservoir areas are detected by Fmask. The average additional part of final water bodies that is detected with the employment of a NDVI-based dynamic threshold for MNDWI is larger than 30 % for all Jordan reservoirs, and can reach more than 50 % for Tanour and Wala reservoirs. Similarly, the average additional part obtained through the 3D reconstruction is larger than 3.9 % (Karama reservoir), and goes beyond 16 % for the more recent reservoirs Tanour, Wala and Mujib, whose construction ended after 2002 – proportionally, more Landsat 7 images affected by “N/A” stripes were then used for them than for older dams. In light of these large

Reservoir	Fmask classification [%]				Changes [%]	
	Water	Land	Other	N/A	2D	3D
El Wahda	58.6	20.8	13.1	7.5	32.2	9.2
Karama	64.1	13.3	20.9	1.7	32.0	3.9
Kafrein	58.5	15.9	17.2	8.4	31.9	9.7
Tanour	31.3	15.4	39.0	14.3	52.5	16.1
King Talal	59.4	22.1	9.7	8.8	30.8	9.8
Wala	30.0	24.4	30.0	15.7	52.6	17.5
Mujib	36.1	9.6	37.2	17.2	45.2	18.6

**Table 3.** Initial Fmask classification inside the final water areas (“Other” refer to clouds, cloud shadows and snow), and stages’ percentage changes that led to the classification as water (“2D” for the 2D classification enhancement, and “3D” for the 3D reconstruction).

shares of hidden or undetected water areas, corrections were obviously essential to consistently monitor reservoirs elevation and storage.

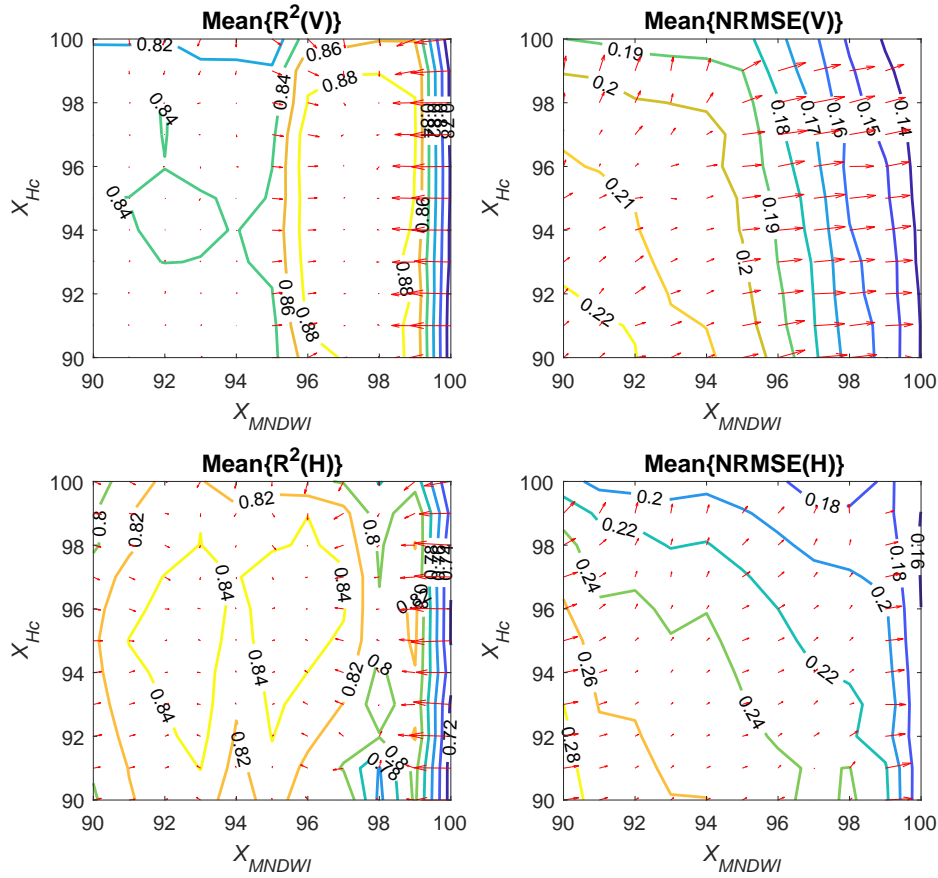
### 3.2 Sensitivity analysis

The two algorithms used to improve the estimation of reservoirs area rely on one empirical threshold each: the classification enhancement is performed through the definition of a MNDWI percentile threshold ( $X_{\text{MNDWI}}$ ) to build a mask dynamically adapted to each Landsat image, and the reconstruction is achieved with the choice of a percentile for  $H_c$  values ( $X_{H_c}$ ), which is set to avoid water areas overestimation.

The sensitivity of the whole method to these two parameters is tested in terms of the above defined indices:  $R^2$  and  $\varepsilon_m$  NRMSE, that are averaged for all reservoirs in Jordan (King Talal excluded). The sensitivity analysis is conducted by making the percentile thresholds vary between 90 and 100 with a step of 1. Results are presented for both storage and elevation in Fig. 1112.

The coefficient of determination reaches its maximum with  $X_{\text{MNDWI}}$  values around 98 for storage and 93 or 95 for elevation. However,  $R^2$  does not quantitatively assess the accuracy of the method, and as it remains fairly high (above 0.78 for storage, or 0.74 for elevation) in the whole 90–100 range for both parameters, it is not considered to select the threshold percentiles.

In addition,  $|\varepsilon_m|$  NRMSE decreases as  $X_{\text{MNDWI}}$  and  $X_{H_c}$  increase. The method does not detect an excessive number of water pixels – see the retrieval over the large missing parts detailed in Table 3 –, but rather obtains estimates for elevation and storage closer to the measurements conducted by JVA. Two conclusions can be drawn from these observations. First, the success in the 2D enhancement means that there is enough information in Landsat bands to better detect water areas. And second, the precision of the 3D reconstruction implies that enough Landsat images are available for most reservoirs to statistically improve the detection of water bodies when clouds or “N/A” stripes hide land.



**Figure 12.** Sensitivity analysis of the two thresholds used to improve water bodies surface area estimates. Indices are averaged for all Jordanian reservoirs (except King Talal). Arrows point towards larger  $R^2$ , or lower  $|\epsilon_m|NRMSE$ , and lengths are proportional to the gradient.

However, the  $H_c$  upper limit for the reconstruction has a decreasing impact on  $|\epsilon_m|NRMSE$  as the MNDWI threshold increases: fewer missing water pixels leads to fewer pixels available to “fill with water” during the subsequent reconstruction. For lower  $X_{MNDWI}$  values, the decrease in  $|\epsilon_m|NRMSE$  for high  $X_{H_c}$  values is clearer. It shows that the reconstruction algorithm addresses well the Fmask and dynamic threshold method limitations, even if it cannot entirely balance the errors. The fact that  $|\epsilon_m|NRMSE$  is on average lower for maximal  $X_{H_c}$  values than for maximal  $X_{MNDWI}$  values could however be expected as the reconstruction relies on the reservoir’s elevation-area relationship, which is established from the elevation of the pixels that are detected in the first stage.

In the end, the percentiles that we chose in this study – respectively 100 and 98 for  $X_{MNDWI}$  and  $X_{H_c}$  – enable a trade-off between the options of lowering  $|\epsilon_m|NRMSE$  for both storage and elevation. Also, with these percentiles,  $R^2$  is still significantly high to ensure a strong correlation. It should be noted that the thresholds do not depend on the location, nor the date the Landsat



images were taken. Therefore, the sensitivity analysis reveals that highest values for both  $X_{MNDWI}$  and  $X_{H_c}$  could be used to apply the method to any other region in the world.

#### 4 Conclusions

Although information on small reservoirs storage is crucial for water management in a river basin, it is most of the time not freely available in remote, ungauged or conflict-prone conflict-torn areas. A remote sensing method is proposed in this paper to monitor small water bodies (capacities and water surface areas starting from 1 hm<sup>3</sup> and 0.5 km<sup>2</sup> respectively). The method is based only on DEMs for elevation, and Landsat satellite images for water surface area, to quantitatively estimate storage variations.

The method is applied to reservoirs in Syria and the Israel-controlled Golan Heights in the Yarmouk River Basin, and an uncertainty analysis is conducted with neighbouring Jordan reservoirs for which *in situ* measurements are available. The average relative error NRMSE is relatively low compared to the size of the studied reservoirs and the precision of the datasets that are used.

The main limitation of the approach is its inapplicability to reservoirs that were significantly “covered” with water when the DEM satellites passed over them. Fortunately, this information can be readily obtained from remote sensing data and used to determine the applicability of the method *a priori*.

For all “uncovered” small or large reservoirs, the uses of datasets available over the whole continental surface, and of make this method a valuable complement to satellite altimetry to increase the number of reservoirs observable anywhere in the world. The thresholds dynamically defined for both the 2D enhancement and the 3D reconstruction, also make the method potentially suitable to monitor reservoirs in truly inaccessible areas. Moreover, the precision of the filling curve and the 3D reconstruction algorithm increases with the number of pixels taken into account. Applying the method to large “uncovered” reservoirs could then potentially lead to better results. The sensitivity analysis also shows that choosing maximum thresholds in both water area retrieval stages gives the best reservoir storage estimates.

The recent two Sentinel-2 satellites also promise a great improvement of the method for post-2015 studies, as they produce images with spatial and temporal resolutions finer than Landsat (up to 10 m and 5 days). Combining Landsat and Sentinel-2 satellites would then reduce the already short revisit cycle of water bodies and would provide near real-time updates on water bodies storage.

Furthermore, the algorithms used in the method automatically detect water bodies, define the water areas retrieval parameters, build filling curves and assess reservoir storage. They could thus provide near real-time updates on water bodies storage. Indeed, Landsat images are produced every 16 days (or 8 days for parts covered by several scenes with different WRS), and Such algorithmic tools can then be dynamically updated with each new image provides additional information to the algorithmic tools that can then learn by themselves from Sentinel-2 and Landsat satellites, giving the model the potential to learn by itself and correct previous storage estimates while generating new ones. This approach is somehow comparable to the continuous change detection proposed by Zhu and Woodcock (2014).

*Code and data availability.* [The source code of the algorithm is available at https://drive.google.com/open?id=0B54cRCK06X-9RUdqaTZmWkdsOXc](https://drive.google.com/open?id=0B54cRCK06X-9RUdqaTZmWkdsOXc). Underlying research data are not publicly accessible. Remote sensing data access for this study is explained in Sect. 2. JVA data records are not publicly available.

*Competing interests.* The authors declare that they have no conflict of interest.

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