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Discussions

Interactive comment on "Monitoring small reservoirs storage from satellite remote sensing in inaccessible areas" *by* Nicolas Avisse et al.

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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

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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" (p4, l12) 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, l1-2): "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, l10): "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 et al., 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 criteria) 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, l3-13), 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, l5-7): "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, l8): "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, l4-7). 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 (p13, l11-12): "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 (p14, l1-2): "**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 3, 4 and 8. We have also added North and East indices to the legend to match common representation of satellite images (e.g., Frappart et al., 2006; Gao et al., 2012; Zhang et al., 2014; Crétaux, 2015). The title "Inundation frequency" is now also 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 < N < 35, see p16, l10) and not necessarily conducted at the same time as storage measurements, the relationships could not be retrieved with precision.

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