Deutsches Geodätisches Forschungsinstitut
Ingenieurfakultät Bau Geo Umwelt
Technische Universität München

Estimation of gap-less time series of inland waters' surface areas using Landsat and Sentinel-2

Christian Schwatke (christian.schwatke@tum.de), Daniel Scherer

Deutsches Geodätisches Forschungsinstitut der Technischen Universität München (DGFI-TUM)

1. Introduction

In the frame of climate change, the knowledge of the continental water cycle plays an important key role. For such investigations, hydrologists mainly require information about lake volume changes and river discharge which can be achieved nowadays by using remote sensing data. On the one hand, water level time series can be already derived successfully from satellite altimetry, on the other hand, surface area information can be derived from optical images.

In this poster, the "Automated Water Area Extraction Tool" (AWAX) for inland waters is presented. AWAX provides monthly water surface area time series for users independently of their remote sensing knowledge and experience.

2. Data

For the computation of surface area time series of lakes and reservoirs, optical images derived from Landsat-4 (07/1982 – 12/1993) , Landsat-5 (03/1984 – 06/2013), Landsat-7 (since 04/1999), Landsat-8 (since 02/2013), Sentinel-2A (since 06/2015) and Sentinel-2B (since 03/2017) are used. In this study, we use optical images between January 1984 and June 2018.

3. Methodology

The AWAX approach of estimating gap-less surface area time series is based on a land-water classification using five different water indexes, and a gap-filling step using the derived long-term water probability mask. More details can be found in Schwatke et al, 2019. The detailed flowchart of the AWAX approach is shown in Figure 1.

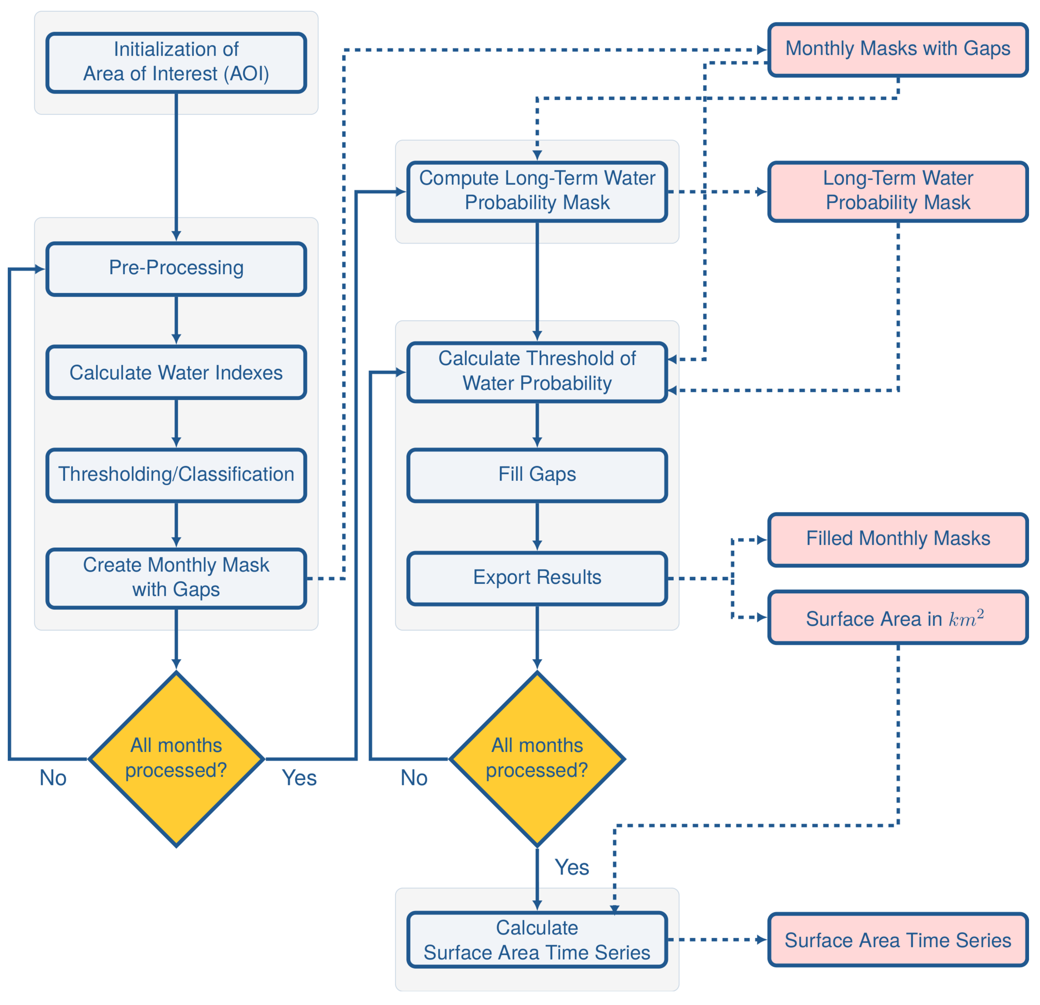

Figure 1: Flowchart of the AWAX approach

In the first step, all available optical images are merged on a monthly basis in order to achieve a monthly composite with reduced data gaps. For the land-water classification, six spectral bands are used. Furthermore, a quality mask containing data gaps caused by voids, clouds, cloud shadows and ice/snow is created.

For the computation of monthly land-water masks the following water indexes are used:

- *Modified Normalized Difference Water Index* ($MNDWI$) [Xu, 2006]
- *New Water Index* (NWI) [Ding, 2009]
- *Automated Water Extraction Index for Non-Shadow Areas* ($AWEI_{nsh}$) [Feyisa et al., 2014]
- *Automated Water Extraction Index for Shadow Areas* ($AWEI_{sh}$) [Feyisa et al., 2014]
- *Tasseled Cap for Wetness* (TC_{wet}) [Kauth et al., 1976]

Based on the five water indexes a joined threshold computation is performed.

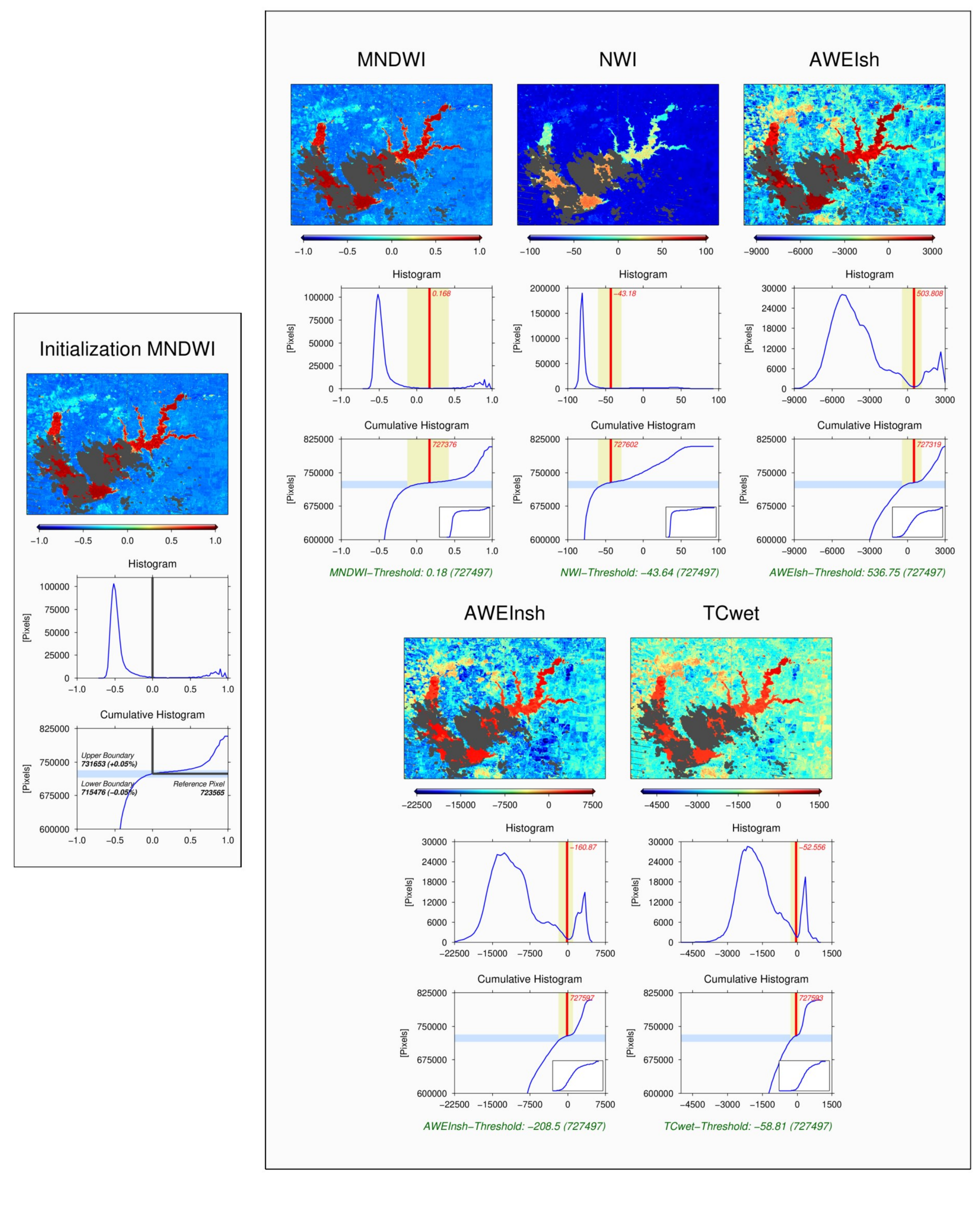

Figure 2: Threshold computation using five water indexes in order to achieve five binary land water masks for Ray Roberts in January 2007

Then, all five water resulting land-water masks are accumulated in order to achieve a monthly land-water mask with data gaps.

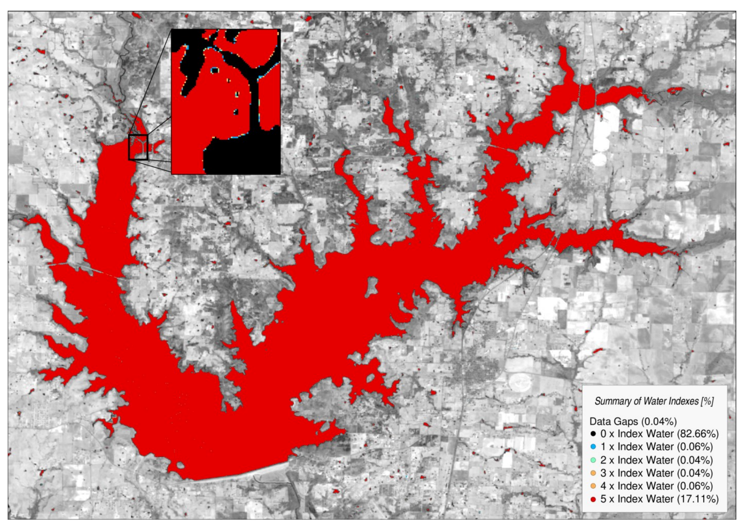

Figure 3: Merged monthly land-water mask with remaining data gaps and uncertainties shown for Ray Roberts in January 2017; created by accumulating five land individual land-water masks.

In the next step, the data gaps are filled by using a long-term water probability mask derived from all monthly land water masks in the period between January 1984 and June 2018 shown in Figure 4. Furthermore, the dependency between water probability and area extent is used.

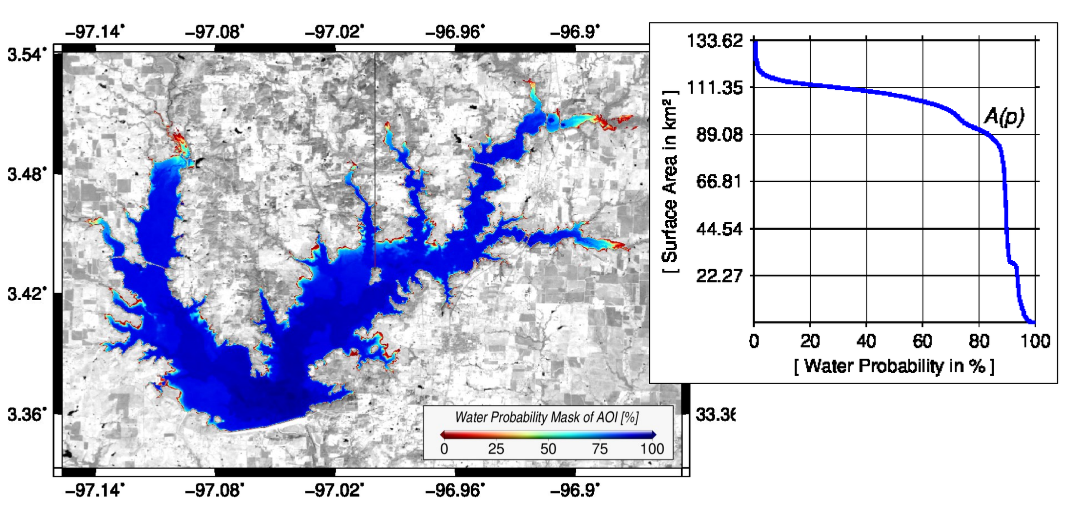

Figure 4: Long-term water probability mask between January 1984 and June 2018 for Ray Roberts reservoir. Additionally, the dependency between surface area and water probability is shown.

The data gaps in all monthly composites are filled in an iterative approach by minimizing the following equation in order to find the best water probability p.

$$|(A_{initial} + A_{fill}(p)) - A(p)| \stackrel{!}{=} Min$$

Here, $A_{initial}$ is the surface area of all visible water pixels which is constant for each month. A_{fill} is the iteratively computed surface area of all water pixels depending on p. Then the sum of $A_{initial}$ and A_{fill} is minimized with respect to the surface area depending on p which is derived from the long-term water probability mask.

The resulting filled monthly land-water mask for Ray Roberts in October is shown in Figure 5. Finally, all monthly surface areas are computed to achieve a final surface area time series.

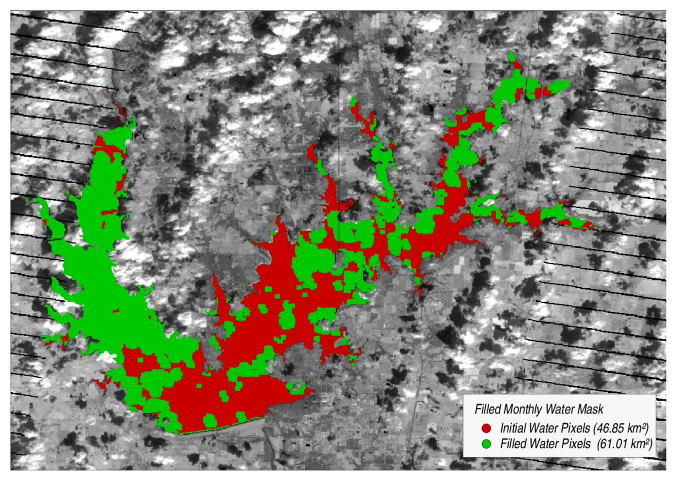

Figure 5: Final monthly land-water mask with initial water pixels (red) and filled water pixels (green)

4. Results and Validation

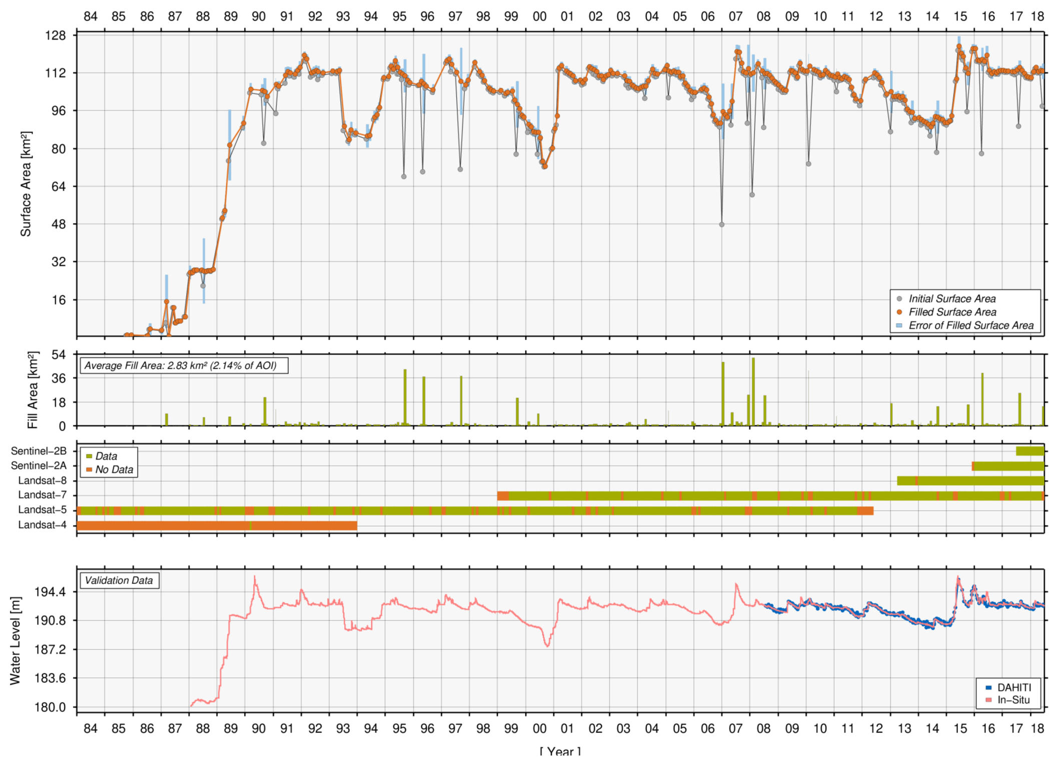

Figure 6: Resulting surface area time series (orange) and initial surface areas (gray). Furthermore, filled areas, used data and validation data are shown.

For validation, water level time series from satellite altimetry and in-situ stations are used. Figure 6 shows the scatter plot between initial and final surface area time series and water level (in-situ and altimetry-based). The correlation increased from 0.763 to 0.937 respectively 0.923.

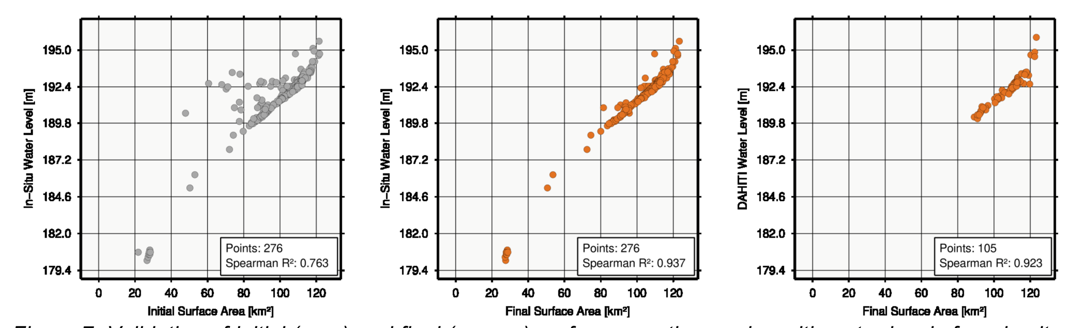

Figure 7: Validation of initial (gray) and final (orange) surface area time series with water levels from in-situ data and satellite altimetry

5. Conclusion

In this study, 32 globally distributed study areas have be investigated in detail [Schwatke et al., 2019]. The average correlation coefficients R² between surface area time series and water levels from in-situ and satellite altimetry have increased from **0.611** to **0.862** after filling the data gaps which is an improvement of about **41%**.

6. Data Access

Currently, more than **50** surface area time series are freely available on the website of the "Database for Hydrological Time Series of Inland Waters" (DAHITI) on

http://dahiti.dgfi.tum.de.

References

- *Ding, F.:* **Study on Information Extraction of Water Body with a New Water Index (NWI).** Science of Surveying and Mapping 2009, 34, 155–157.
- *Feyisa G.L., Meilby H., Fensholt R., Proud S.R.:* **Automated Water Extraction Index: A new technique for surface water mapping using Landsat imagery**. Remote Sensing of Environment 2014, 140, 23 – 35.
- *Kauth R., Thomas G.:* **TheTasseled Cap - A graphic description of thespectral-temporal development of agricul-tural crops as seen by Landsat.** Proceedings of the Symposium on Machine Processing of Remotely Sensed Data, Purdue University, West Lafayette 1976, 4B, 41–51.
- *Schwatke C., Scherer D., Dettmering D.:* **Automated Extraction of Consistent Time-Variable Water Surfaces of Lakes and Reservoirs based on Landsat and Sentinel-2.** Remote Sensing, 11(9), 1010, doi:10.3390/rs11091010, 2019
- *Xu, H.:* **Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery**. International Journal of Remote Sensing 2006, 27, 3025–3033.

ESA Living Planet Symposium, Milan, Italy, 13-17 May 2019