EO Clinic project:

Surface Water Mapping in Kazakhstan

Work Order Report

Support requested by:
Asian Development Bank (ADB)

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ABOUT THIS DOCUMENT

This publication was prepared in the framework of the EO Clinic (Earth Observation Clinic, see below), in partnership between ESA (European Space Agency), the Asian Development Bank (ADB) and team of service providers contracted by ESA: e-Geos (Italy), DHI Gras (Denmark) and IsardSAT (Spain).

This Work Order Report (WOR) describes the context of the ADB activities on *Surface Water Mapping in Kazakhstan*, the geoinformation requirements of the activities and finally, the EO products and services delivered by the EO Clinic service providers in support of those activities.

ABOUT THE EO CLINIC

The EO Clinic (Earth Observation Clinic) is an ESA (European Space Agency) initiative to create a rapid-response mechanism for small-scale and exploratory uses of satellite EO information in support of a wide range of International Development projects and activities. The EO Clinic consists of “on-call” technically pre-qualified teams of EO service suppliers and satellite remote sensing experts in ESA member states. These teams are ready to demonstrate the utility of satellite data for the development sector, using their wide range of geospatial data skills and experience with a large variety of satellite data types.

The support teams are ready to meet the short delivery timescales often required by the development sector, targeting a maximum of 3 months from request to solution.

The EO Clinic is also an opportunity to explore more innovative EO products related to developing or improving methodologies for deriving socio-economic and environmental parameters and indicators.

The EO Clinic was launched in March 2019 and is open to support requests by key development banks and agencies during the 2 years project duration.

AUTHORS

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The following colleagues provided valuable inputs, insights and evaluation feedback on the work performed: Paolo Manunta (Senior Infrastructure EO Specialist, Asian Development Bank), and Zoltan Bartalis (ESA Coordinator and Technical Officer).

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1 DEVELOPMENT CONTEXT AND BACKGROUND

Despite the aridity of the climate, floods are quite frequent in Kazakhstan. Several hundreds of floods caused by different phenomena (e.g. spring thaw and rainfall) have been recorded in Kazakhstan over the past decades. Still, the problem of flooding, and above all the issue of full-scale protection against its destructive impact, are yet to be resolved. By example, recent studies from the capital Nur-Sultan (formerly known as Astana) show that infrequent floods along river Ishim can reach extremely high-water levels with potential damaging effects on the infrastructure, human life's and livelihoods and ultimately impacting Kazakhstan's commitment the 2030 agenda on Sustainable Development.

Therefore, the Committee on Water Resources of the Ministry of Ecology, Geology and Natural Resources and the Committee for Emergency Situations of the Ministry of Internal Affairs has appointed the national space agency (Kazakhstan Gharysh Sapary - KGS) to provide solutions to mitigate flood-related hazards and risks.

The application of Earth Observation data is a very efficient and cost-effective way to support flood protection programs. EO can be used for large-area and high-temporal monitoring of all water bodies (i.e. inland and coastal, lakes/reservoirs and rivers) in both extent and volume – information of direct relevance for better understanding the water balance incl. the relationship between reservoir water levels and flood occurrence as well as for ingestion into hydrodynamic models to improve flood simulations.

The overall objective of this RFP is to provide KGS (national space agency) with EO-based information that may help to improve flood simulation and calculation of water volume in reservoirs for the Nura and the Ishim river basin, and ultimately support flood protection programs and likewise corresponding risk assessments;

The activity is carried out within the scope of the recent ADB Knowledge and support Technical Assistance (KSTA) focusing on streamlining the use of high-level technologies in Kazakhstan and aligned with the operational priorities for ADB country partnerships and the National Sustainable Development Strategy of Kazakhstan.

2 PROPOSED WORK LOGIC FOR EO-BASED SOLUTIONS

Several different EO products and associated deliverables will be produced under this procurement, including:

- Full-scale detection of the inundation frequency from 2017 to 2019 and covering the entire area of Ishim and Nura river basins (~300.000 km2). [ii] In a second step we will complement the recent epoch with a historical mapping of surface water dynamics and using the full Landsat archive (+ 30 years).
- Water levels from altimetry over selected water bodies and with a focus on the Intumak and Samarkand reservoir area as well as the area around Nur-Sultan.
- Individual water body dynamics from where altimetry derived water levels data is available

We note that the analysis is limited to the ice-free (i.e. open water) period of Northern Kazakhstan corresponding the period from April to October.

Figure 1 illustrates the overall service workflow and the service interrelations, while the specifications and approach for development and implementation of those services as well as the online portal are described in the following sections.

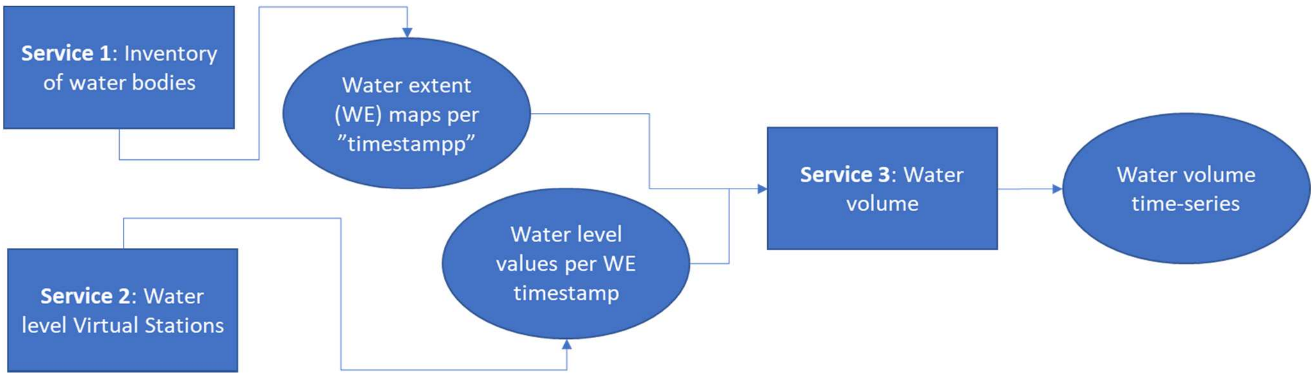


Figure 1. Service workflow.

The key focal areas for the EO services are illustrated in Figure 2. As per recommendation in the RFP the Area of Interest (AOI) has been refined and further detailed using the area information provided and the catchment boundaries from the Hydrobasins dataset (https://www.hydrosheds.org/page/hydrobasins). In doing so we propose a total AOI that consist of the Kazakhstan part of the Ishim and Nura basin, and extended with a small part of the Ob river basin to include also Lake Tengiz.

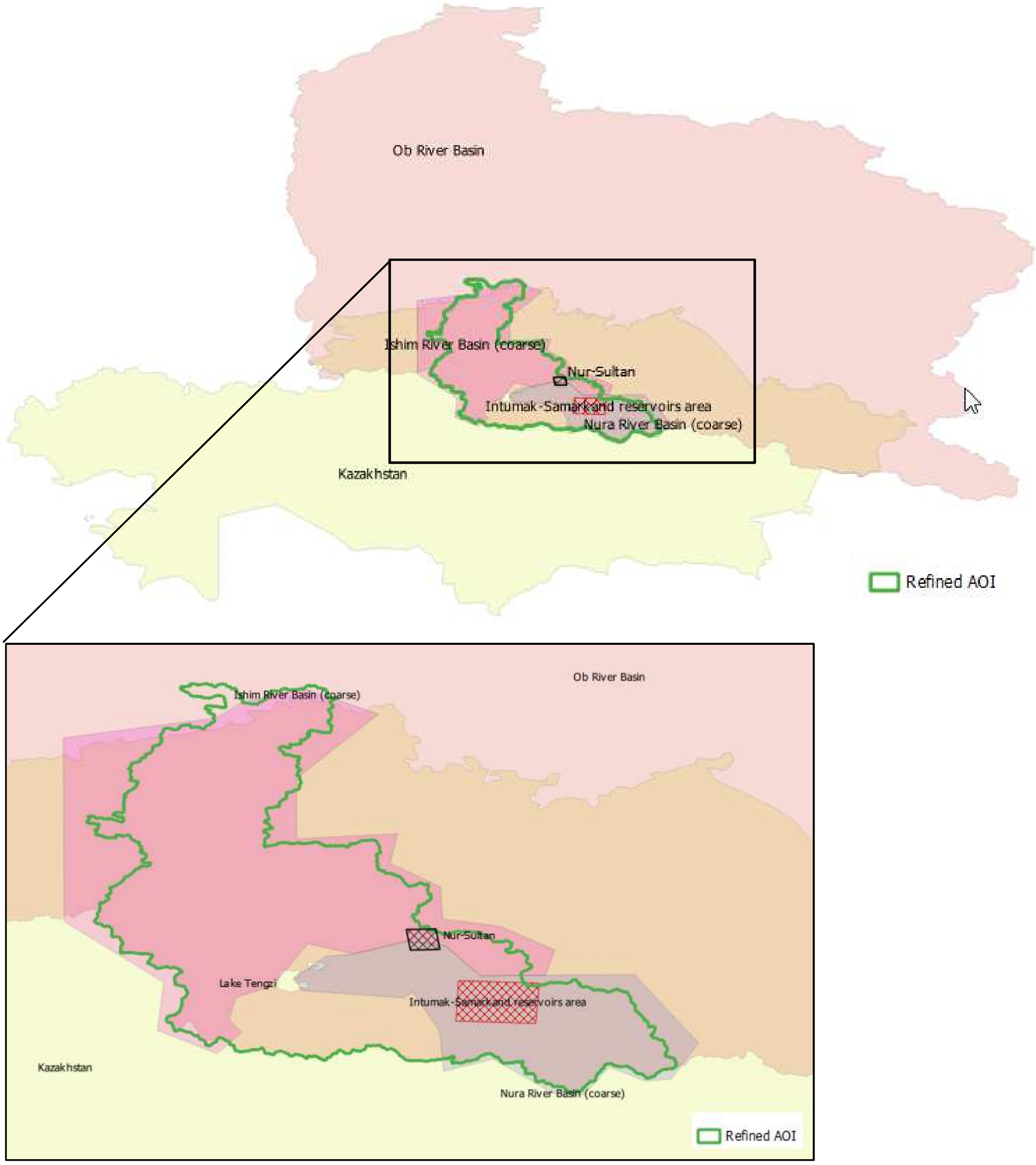


Figure 2. The refined AOI relative to the approximate areas provided as part of RFP.

The results presented in this report are final i.e. they represent the stage of development and production achieved at the end of the procurement. Further, refinements and potential additional datasets will be considered in response to comments and/or clarifications arising from the final video conference to be scheduled with ESA and the Kazakhstan counterparts.

3 DELIVERED EO-BASED PRODUCTS AND SERVICES

3.1 Service 1: Inventory of Water Bodies and Associated Dynamics

This service shall provide a detailed mapping of the annual variations of the surface water dynamics (frequency and minimum and maximum water extent) in the Ishim and Nura river basins. The water frequency for the most recent period and as mapped form a synergistic use of sentinel-1 and Sentinel 2 is shown in Figure 3 and Figure 3. The long-term water presence as deducted from Landsat imagery and indicating minimum and maximum water extent is shown in Figure 5 for the region around Nur Sultan. What the maps show is a high inter as well as intra-annual variation in surface water extent also indicating the importance of understanding this variability better in order to support flood protection and mitigation.

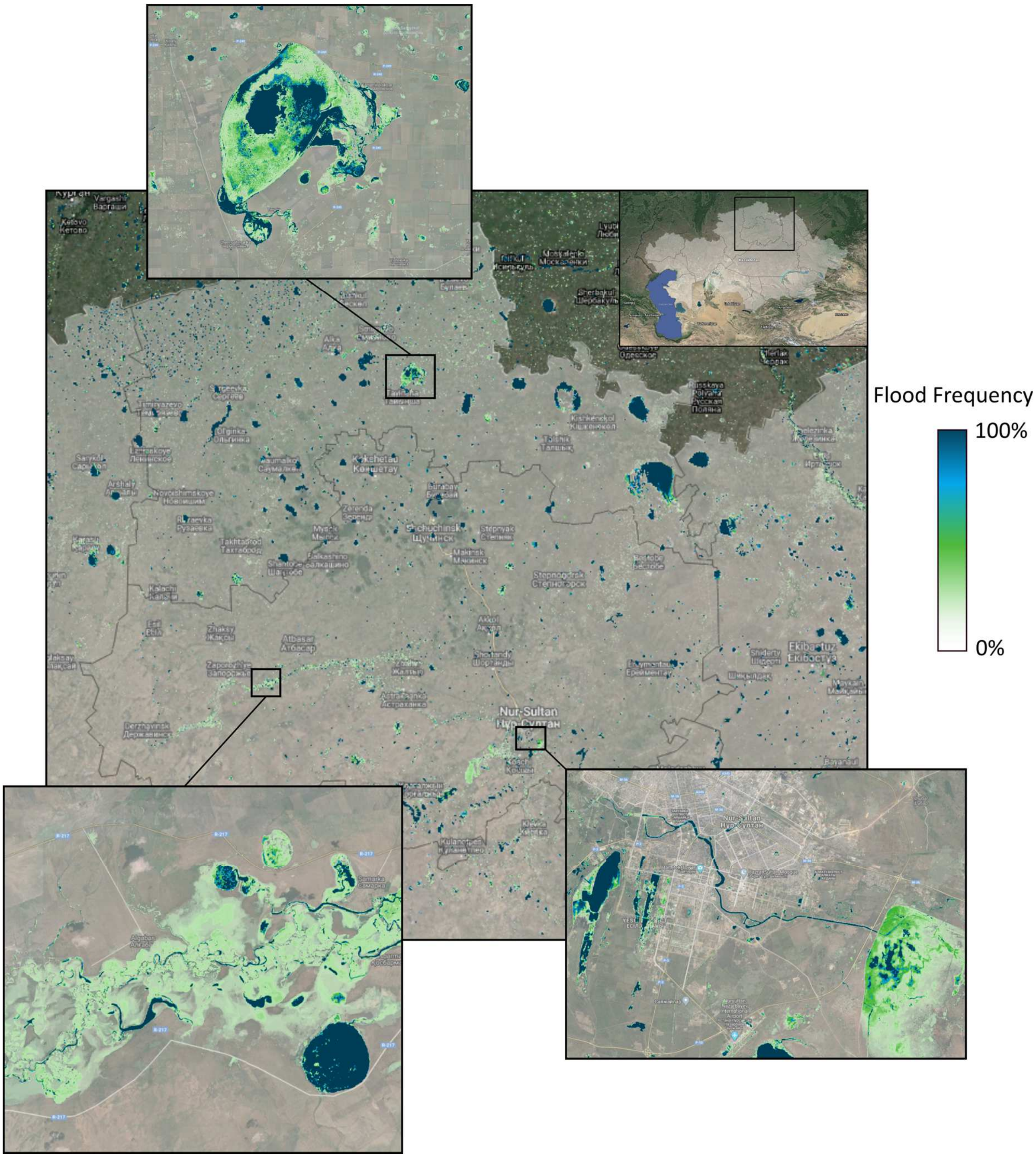


Figure 3. The water frequency map for 2017 to 2019 for the Ishim and Nura river basins. Inserted zooms of: Norther Kiyma (lower left); Samarkand reservoir (top right) and Nur Sultan (lower left).

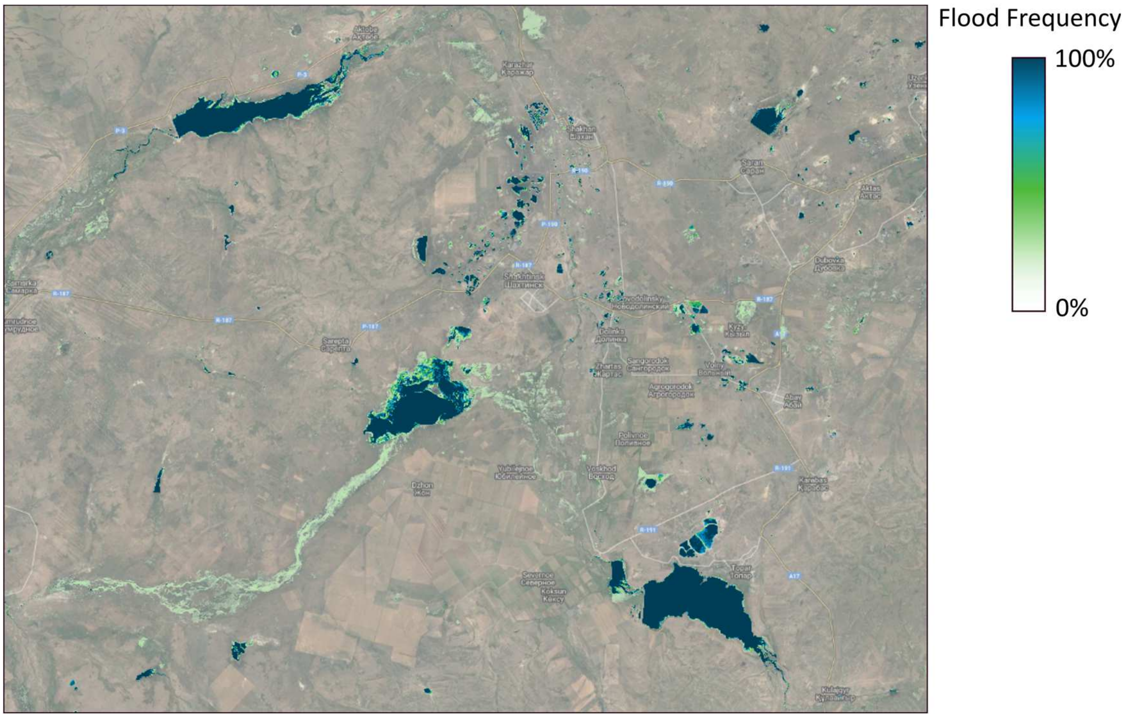


Figure 4. The water frequency map for 2017 to 2019 for Intimak (top) Sasykkol (middle) and Sherubaynurinskoe (bottom) reservoirs (lower left).

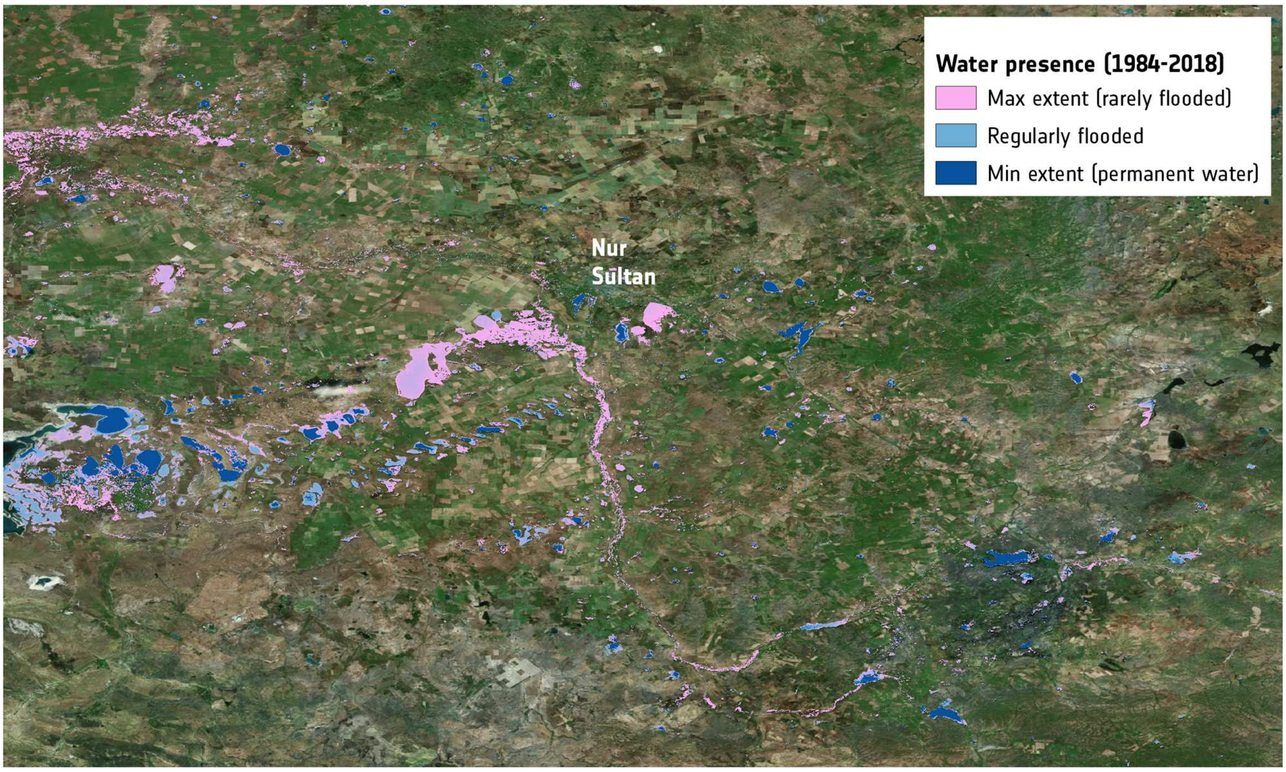


Figure 5. Minimum and maximum water extent observed around Nur Sultan over the 1984 to 2018 time period (modified GSWE).

3.1.1 Specifications

Technical specifications for the water body dynamics product is summarized below and with the details of the image processing and applied classification model provided in the following sections.

EO input data: Sentinel-1, Sentinel-2

Other input data: Digital Elevation Model (<30m resolution)

Method: The water extent maps are derived using a supervised machine learning algorithm (i.e. Random Forest) that takes a set of training data to establish the relationship between the response variable (i.e. water class) and the explanatory variables (cf. the satellite imagery). The model uses the full temporal resolution of the Sentinels to generate monthly water masks. Water frequency parameters (annual min/max extent and multi-annual freqancy and min/max extent) are derived subsequently to give a comprehensive representation of the surface water variations throughout one year.

Output indicators: Minimum and maximum water extent; Water frequency

Map legend: Categorical classification (dry, minimum and maximum water extent), Water frequency [%]

Spatial resolution: 10 m pixel resolution. MMU = 0.1ha = 3 pixels

Temporal resolution: Monthly, 2017-2019

Delivery format: GeoTiff, QGIS style file, additional information or other data formats upon request

3.1.1.1 Image processing

The significant datasets used for this project are optical and SAR satellite data from Sentinel 2 and Sentinel-1 for the 2016-2019 time period and optical Landsat imagery for the long-term historic monitoring. Before conducting the image analyses, essential pre-processing of the acquired data was conducted. The basic outline of the processing steps is given in below.

The Multi-Spectral Instrument (MSI) onboard Sentinel-2 acquires 13 spectral bands ranging from visible and near-infrared (VNIR) to shortwave infrared (SWIR) wavelengths along a 290-km orbital swath and a spatial resolution of 10 m (four visible and near-infrared bands), 20 m (six red edge and shortwave infrared bands) and 60 m (three atmospheric correction bands) (cf. Figure 6)

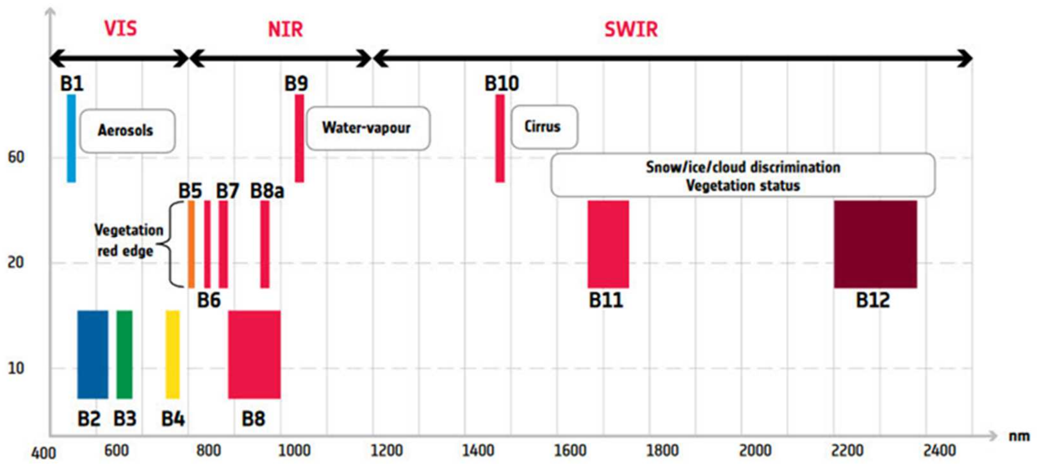


Figure 6. Spatial resolution versus wavelength of the Multi-Spectral Instrument (MSI) onboard Sentinel-2 (source: ESA).

We used all the bands with 10- and 20-meter spatial resolution. We applied Top of the Atmosphere (TOA) correctio to the data, and the 20-meter bands were resampled to 10 meters. In order to remove the cloudiest images from the time series, only images with a cloud cover less than 20% (according to internal quality flags) were retained for the analysis. Masking of remaining clouds and cirrus as well as cloud shadows and snow were done by FMASK.

Thereafter, spectral indices were calculated based on combinations of the Sentinel-2 reflectance bands. Spectral indices are useful to highlight specific properties relevant for water detection (cf. Table 1)

Table 1. Sentinel 2 spectral indices for water presence prediction

Index	Short name	Equation [Sentinel-2 bands]
Normalized Difference Vegetation Index	NDVI	("B8") - ("B4") / ("B8") + ("B4")
Normalized Difference Water Index	NDWI	("B8") - ("B11") / ("B8") + ("B11")
Modified Normalized Difference Water Index	mNDWI	("B11") - ("B3") / ("B11") + ("B3")
Normalized Multi-band Drought Index	NMDI	("B11") - ("B12") - ("B8") / ("B11") - ("B12") + ("B8")
Normalized Difference NIR - SWIR2	ND0812	("B12") - b("B8") / ("B12") + ("B8")
Normalized Difference BLUE - RED	ND0204	("B4") - ("B2") / ("B4") + ("B2")

From the Sentinel-1 dataset, we used Level-1 Informetric Wide Swath (IW) and Ground Range Detected (GRD) data. The data have been processed to generate a calibrated, ortho-corrected product with a 10-meter spatial resolution. The VV and VH backscattering values were used for the water classifications.

All data with a 7-day period are merged and used as input for water mapping.

3.1.1.2 Water mapping

Predicting the extent of water using Earth Observation data relies on 3 key components: 1) training data, 2) machine learning, and 3) post-processing. The approach uses all available data from Sentinel-1, Sentinel-2, and feeds the information into a Random Forest classifier to predict wetland probability.

3.1.1.2.1 Training data

The main requirement of a well-trained classification model is a set of training samples that represent the classes of interest. In this case we had a binary (i.e. 2 classes) classification model which required samples of water and non-water locations, respectively. The training samples were compiled from the JRC Global Surface Water Explorer – GSWE (Pekel et al. 2016). A systematic random sampling approach was used to the generate the training data for the model prediction. First, the entire region was divided into 10x10 km girds and within each grid we used proportional random selection to select sample locations for water and non-water classes. All together 40.000 samples were used to train a random forest classifier

3.1.1.2.2 Machine learning

Random Forest is based on the principles of Decision Tree classification, but instead of relying on one single tree, it creates hundreds of decision trees using random subsets of both the input variables and the training data, making each tree unique. Each tree is created by taking a random subset of samples (cf. training data). At each node of the tree, a random subset of input variables is chosen. Then the tree is split into branches based on the variable that generated the best split. This splitting continues until all the samples reside in pure leaf nodes. The variable that generates the best split is the one that minimizes the sum of the Residual Sum of Squares (RSS) error from the left and right branches:

$$RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Where y_i is the i^{th} value of the variable to be predicted, and $\hat{y}_i$ is the predicted value of y_i.

When given a test sample, each tree makes a prediction, and the prediction with the most votes among all trees is the one that the model chooses. By taking this approach, it transforms the Decision Tree approach from a 'weak learner' to a 'strong learner', resulting in a classifier which is highly robust towards training label noise, while at the same time matching or exceeding the performance of other respected machine-learning algorithms. Another advantage of RF is the flexibility in terms of input data. Continuous variables using completely different scales are readily accepted as combined input. This means the classifier is well suited for fusing SAR, and optical datasets for water classification.

We ran the RF model with 50 trees and a minimum leaf population of 5. We created models for S1+S2 combined, and S1, S2 individually. A pixel-based decision rule used to return the final prediction i.e. if Sentinel-2 and Sentinel-1 is available use the combined S1-S2 model as this is the most accurate. Where there is S2 cloud masking fill this with S1 only predictions. If only S-2, or S-1 use that only.

3.1.1.2.3 Post-processing

A few post-processing routines were implemented to convert the water probability map for each 7-day period into first monthly water masks and secondly into annual/multi-annual water frequencies. The outcome of the Random Forest classifier is a probability estimate (0-100%) for water presence in each 10x10 meter pixel and for each 7-day period. These 7-day predictions are converted into monthly binary products by taking the mean of all predictions within that month and using a combined probability threshold of 75% to separate water from non-water. Water frequencies are then derived by taken the total number binary water predictions over a time period and divides by the total number of observations over the same period and thereby returning a 0-1 percentage of the water frequency within the given period. To reduce 'salt and pepper' noise we applied a minimum mapping unit (MMU) filter to remove solitary and smaller pixel groupings less than 25 pixels (i.e. 0.25 ha).

3.1.2 Quality Control and Validation

The performance of the classification models was initially assessed against a set of independent samples located across the region of interest. We used stratified random sampling to generate an independent set of sample locations. We used the long-term water transition classes in the GSWE product as strata to ensure we are sampling across the continuum from permanent water to non-water, and for each sample location we visually assessed whether the sample belonged to water or non-water. We used measures of accuracy, precision, recall and F1 scores. All measures which can be determined from the confusion matrix. The confusion matrix is a table commonly used as the basis for describing the performance of a classification model on a set of test data for which the true values are known. In the confusion matrix we operate with true positive and true negatives which are the observations that are correctly predicted and therefore shown in green. The confusion matrix also includes false positives and false negatives which represent wrong predictions and hence displayed in red.

Table 1. Confusion matrix comparing the Water Extend Map (predicted) with independent samples visually checked for water/non-water presence (Actual).

	Predicted	
Actual	Water	Non-water
Water	76	11
Non-water	4	67

Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. Accuracy is a good measure of model performance if you have symmetrical datasets, but in this case, non-water is more prevalent than water. It is therefore useful to also look at other parameters such as precision, recall and F1-score to evaluate the model performance. Precision is the ratio of classification model results that correctly predicted water locations (True Positives) to the models total predicted water observations, both correct (True Positives) and incorrect (False Positives). In other words, precision answers the following question: How many of the waters labelled by the model as waters are actually waters? Recall, on the other hand, is the ratio of classification model results that correctly predicted water locations (True Positives) to all observations in the actual water class (Actual Positives). In other words, recall answers the following question: Of all the known waters, how many of those did the model correctly classify as water? F1-Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively, it is not as easy to understand as accuracy, but F1-Score is usually more useful than accuracy, especially if you have an uneven class distribution. Hence, for water mapping, where non-water is more prevalent than water, F1-Score might be a better measure to use as it provides a balance between Precision and Recall.

The RF machine learning models applied in this study showed an accuracy of 91% when compared to independent reference data. The individual classes of water and non-water were mapped with precision accuracies of 95% and 86 %, respectively, while the Recall accuracies were 87% and 94% for respectively water and non-water. Finally, the F1-scores were 91% for water and 90% for non-water (cf.

Table 2).

Table 2. Model performance metrics for the water prediction model.

	Precision	Recall	F1-score
Non-water	86%	94%	90%
Water	95%	87%	91%

Based on the performance metrics we conclude that the acquired data and the implemented classification model provide a solid approach for the spatio-temporal prediction of water in Kazakhstan.

An inter-comparison with the JRC global surface water product was also performed. While not a validation per se this type of comparison represent an equally important part of the product verification, while also providing the justification for using a more costly regionally optimized mapping approach over a readily available global mapping product.

With a documented high classification accuracy in both the GSWE and the current mapping it comes at no surprise that the two products compares well in terms of waterbodies mapped and their seasonal behavior (permanent vs. seasonal). Of particular interest is, however, the much better capture of smaller and narrower bodies by the Sentinel based approach compared to GSWE, which is based on Landsat imagery (cf. Figure 7).

As the GSWE is based solely on optical Landsat imagery, we would also expect a better temporal capture of the water dynamics with the combined Sentinel-1 and Sentinel.2 approach. This added benefit is harder to quantify with now specific details and short-term flooding events, but in Figure 8 we highlight one area where seasonal water is observed in the 2016-2019 period, yet goes undetected in the long-term GSWE recordings.

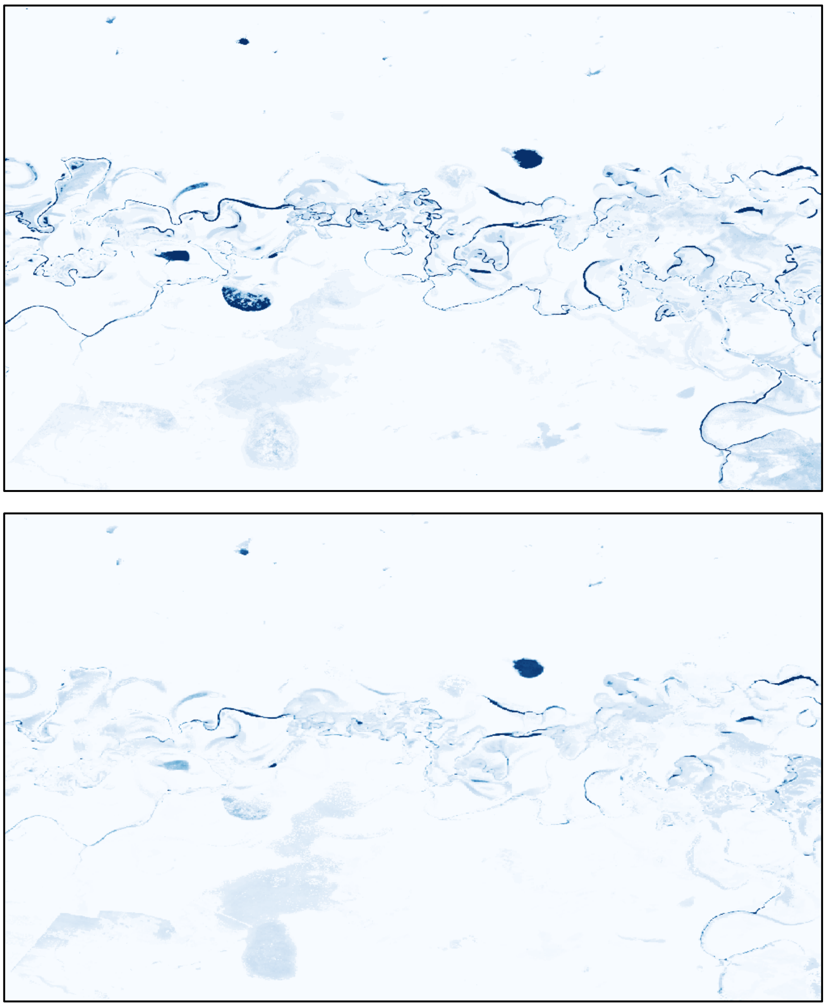
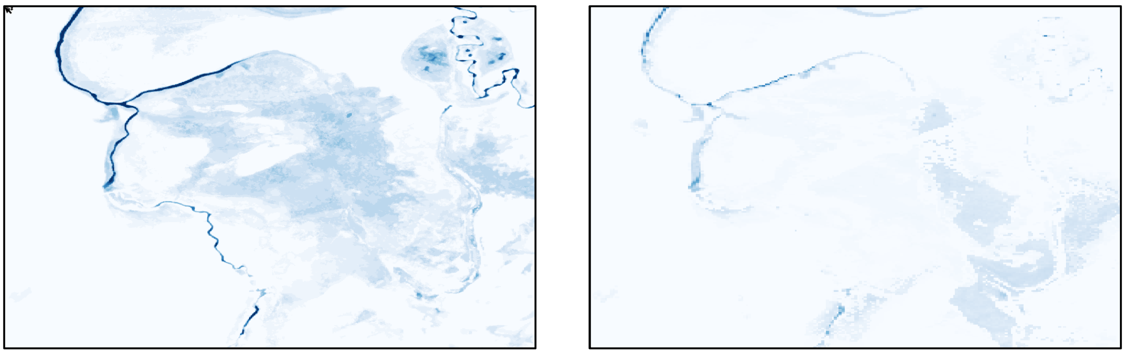


Figure 7. Comparing the recent water frequency map (above) with the GSWE water occurrence map (below).



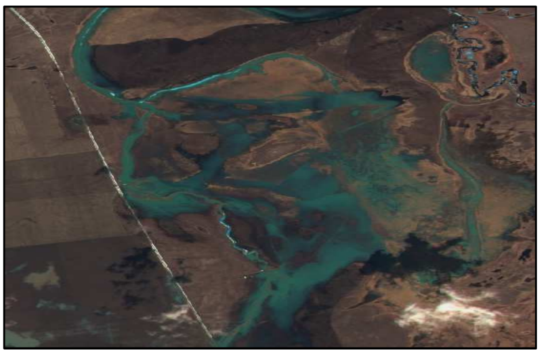


Figure 8. Illustration of flood area captured by Sentinel imagery (top left) but not GSWE (top right) and a Sentinel.2 image from 16. April 2018 (lower left).

3.1.3 Usage, Limitations and Constraints

The water body inventory product contains a detailed mapping of the annual variations of the surface water extent (minimum and maximum water extent) in the Ishim and Nura river basins.

This product serves to characterize the inter- and intra- annual variations of the water extent, and consequently to monitor the dynamics of water retention and flow, and to assess how these changes of water dynamics may affect the overall flooding regime.

In the previous sections we devise a classification approach that consistently maps the water extent at high accuracy in the Kazaksthan part of the Nura and Ishim River basins. In general the detection of water presence in the two river basins are favourable as there are no rugged terrain and cast shadows which can often be confused with water. Still, the known issue of water detection in arid areas with SAR data meant a generally lower performance of the S1 water detector why the S2 predictions were favoured in the monthly fusing of the S1 and S2 water detections. In, addition, residual noise (e.g. from building shadows) often occur and these were supressed by implementing a temporal cleaning filter which removed small groupings of pixels which over time were irregularly classified as water and hence helping to retain small permanent water bodies in the final map.

3.2 Service 2: Virtual Water Level Monitoring Stations

3.2.1 Specifications

Technical specifications for the virtual water level monitoring is summarized below and with the details of the processing provided in the following sections.

EO input data: Jason-2, Jason-3, Sentinel-3A/B, Cryosat-2

Other input data: Surface water mask (GSWE + Service 1)

Method: Water level time series from multi-mission satellite altimetry.

Output indicators: Time series of water level

Units: m

Spatial resolution: Virtual stations

Temporal resolution: Roughly monthly 2017-2019

Delivery format: Ascii (.txt), Excel, shapefile (.shp)

3.2.1.1 Altimetry missions

Inland water levels are measured at certain locations with satellite altimetry data, corresponding to the intersection of the satellite tracks and water bodies, over a continuous time span, are the so-called virtual stations. Altimetry satellite missions considered are Jason 2 and 3, Sentinel 3A and Sentinel 3B as well as Cryosat 2. The temporal coverage of these missions are:

- Jason 2: from 20/06/2008 to 09/10/2019 with a revisit time of 10 days until 10/2016. However, after 07/2017 long repeat orbit and interleaved long repeat orbit have been used which means that the spatial resolution of the mission was very high but the temporal resolution very low (less than once a year).
- Jason 3: since 17/01/2016 with a revisit time of 10 days.
- Sentinel 3A: since 16/02/2016 with a revisit time of
- Sentinel 3B: since 25/04/2018 with a revisit time of 27 days.
- Cryosat 2: since 08/04/2010with a revisit time of 369 days.

3.2.1.2 Virtual stations extraction

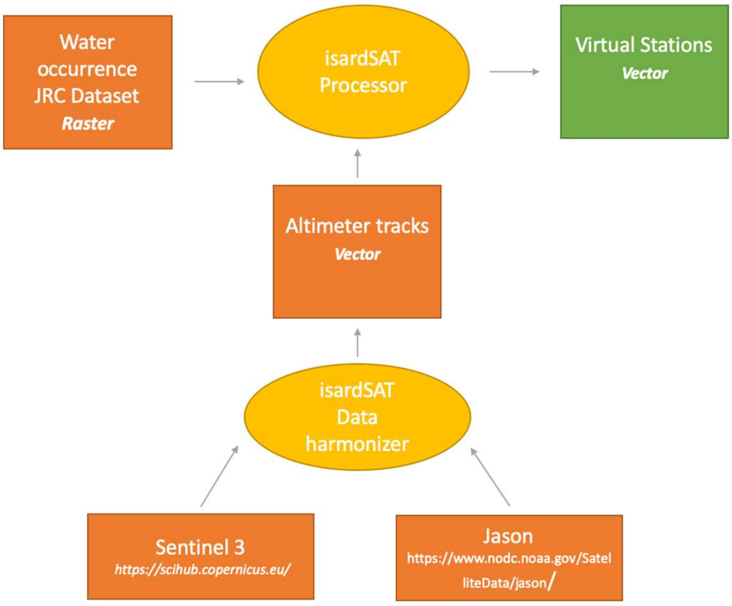


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Figure 9 :isardSAT on-demand Virtual Stations Extractor. Input data (orange), processor modules (yellow), output data(green)

Extracting the virtual stations is carried out automatically in the isardSAT processor without the need of setting them up *a priori,* producing virtual stations on-demand, as requested by users themselves. Data required as input are the water occurrence tiles from the JRC Global Surface Water [1] which express the water occurrence value per pixel in percentage. The resolution of this raster dataset is 30 meters per pixel. The isardSAT processor derives virtual stations by crossing satellite altimeters buffered tracks (depending on the margin of drift from the nominal track) with water occurrence >75%. Nominal reference tracks of the missions are considered. Cryosat 2 tracks are not considered as they can provide only one data point per year but at very high resolution. The potential virtual stations are filtered to only keep the ones with reasonable area to ensure altimeter pulses to fall into the geometry based on the resolution of each altimeter.

Figure 9 details the input and output data necessary for virtual stations extraction processor as well as the data type (raster or vector).

3.2.1.3 Water level processing

Different processors are considered to extract water level time series for this study case. A large scale isardSAT L2 processor derives water level time series based on level 2 data from altimeter passes of the considered missions for the virtual stations computed. Figure 10 explains the data architecture and processor.

[1] https://global-surface-water.appspot.com

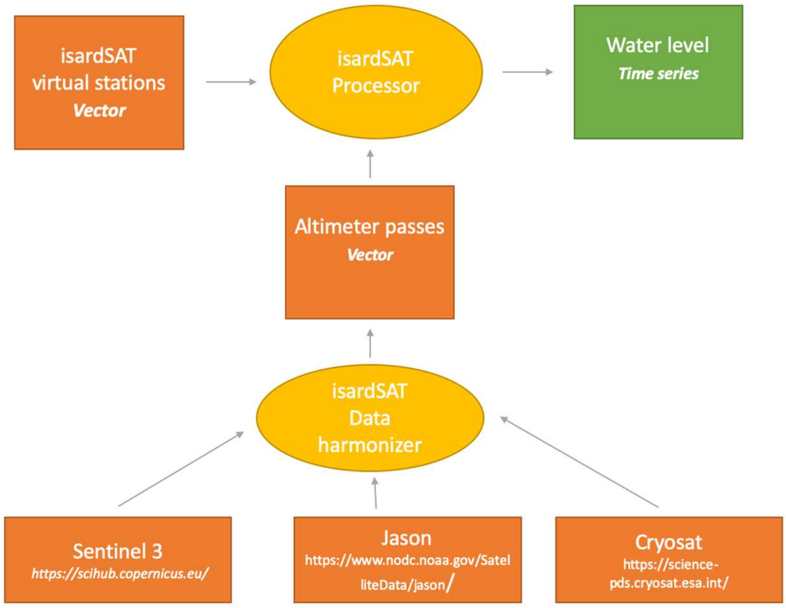


Figure 10: isardSAT on demand Water Level processor Level 2. Input data (orange), processor modules (yellow), output data(green)

Finally, a reservoir of specific interest after first step of processing of water extent time series and water level time series, is re-processed based on a Level 1 isardSAT processor developed in house and presented in in Gao et al. 2019[1]. The level of accuracy is largely improved but not yet operational for on-demand large scale water level processing.

Water level time series outputted present the following features:

- Name of the virtual station
- Date of the acquisition
- Longitude
- Latitude
- Water level value in meters with respect to the geoid EGM2008
- Number of altimetry points falling into the geometry of the virtual stations
- Mission name

3.2.2 Quality control and validation

3.2.2.1 Potential virtual stations

A total count of 737 potential virtual stations for the regions of interest of this case have been derived:

- 351 for S3A
- 379 for S3B
- 7 for Jason

The number of potential virtual stations is:

- 602 for Ishim River basin
- 136 for Nura River basin
- 21 for Intumak-Samarkand

[1] Gao, Qi, Eduard Makhoul, Maria Escorihuela, Mehrez Zribi, Pere Quintana Seguí, Pablo García, and Mònica Roca. 2019.

Figure 11 maps the potential virtual stations for the area of interest (AOI) provided in the study as well as the satellite tracks of each mission but Cryosat 2 as its resolution is very high so the display would be very dense.

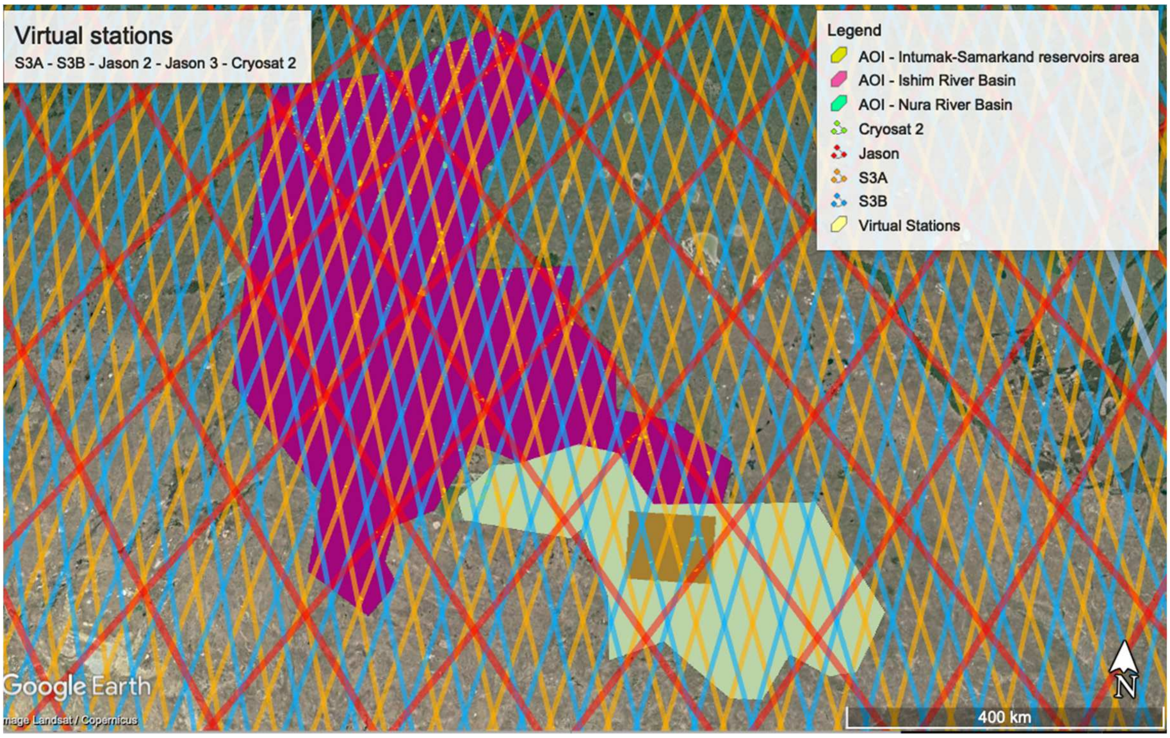


Figure 11: Virtual Stations and satellite tracks in Kazakhstan

For this reason a zoom on the AOI of Intumak-Samarkand reservoirs area is provided with the tracks of Cryosat-2 added in Figure 12.

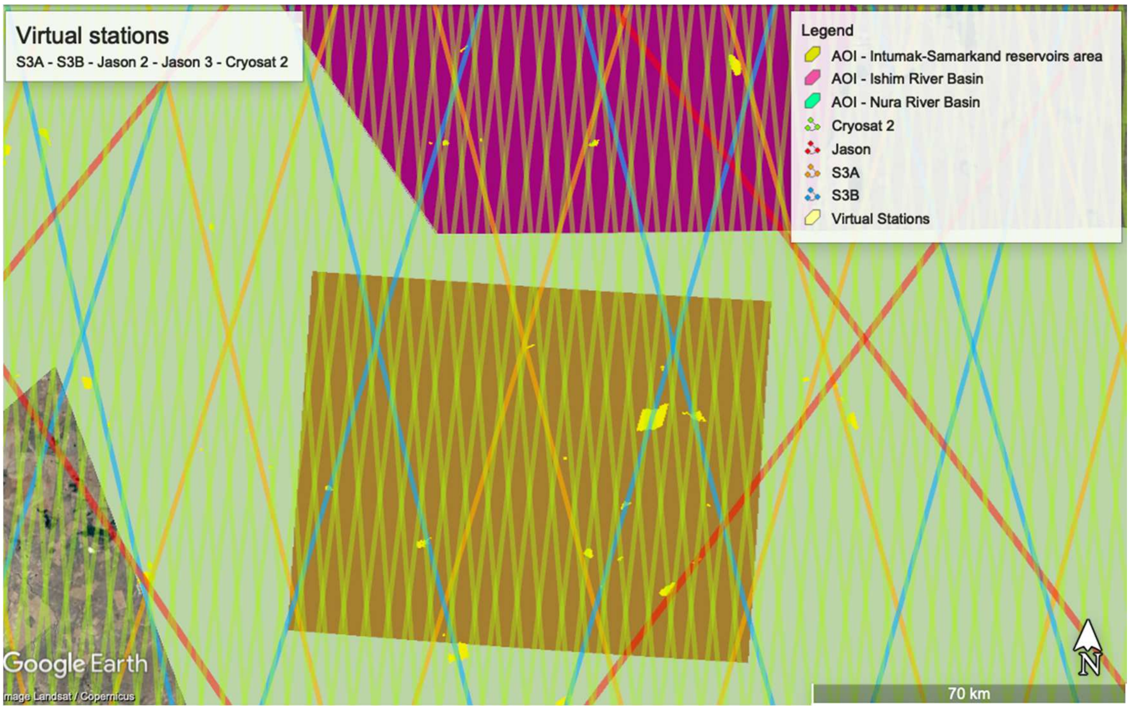


Figure 12: Virtual Stations and satellite tracks of the Intumak-Samarkand reservoirs area

Preliminary results

Two large reservoirs monitored by Sentinel 3 were firstly chosen in this special region of Intumak-Samarkand (Samarkabdskoe and Sasykkol 1) as the area of the virtual stations were large, hence many altimetry points will likely be available. However, the water extent time series analysis revealed a small variation over time, so three other virtual stations have then been considered (Sasykkol 2, Aktobe and Taldykol). Figure 13 shows the display of these virtual stations.

Figure 13: Map of the virtual stations considered

Preliminary results based on Sentinel 3 are shown in the following graphs for each of this virtual station (Figure 14). Note only one value for Aktobe on 25/02/2019 of 452.2636 m is available (not shown). This is due to the shape of the virtual stations which is skimpy and does not allow lots of altimetry points to fall into the geometry.

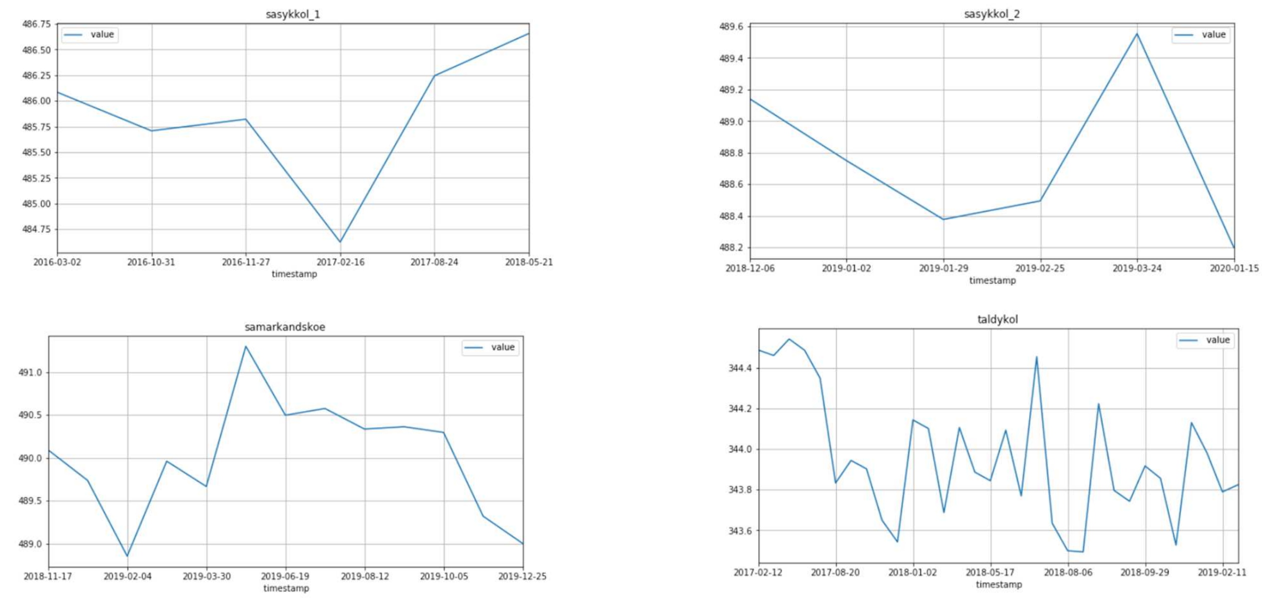


Figure 14. Water level time series for the selected virtual stations. Values are in m over the geoid EGM2008.

As no in situ data have been made yet available to us for these area in Kazakhstan, we provide the results of this algorithm for the reservoir of Sotonera in Spain in Figure 15 with a RMSE=1.32 m and Pearson coefficient of 0.96.

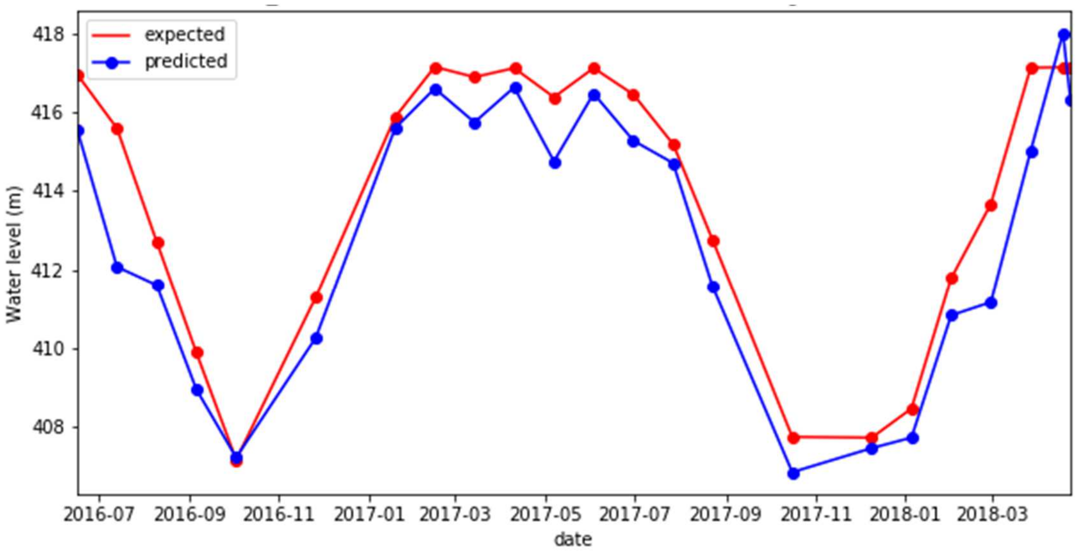


Figure 15- Water level time series in Sotonera. isardSAT processer (blue), in situ data (red).

This performance can largely be improved by the isardSAT processor L1 level implementing Gao et al. 2019 which reaches a RMSE of 0.60m for this same reservoir of Sotonera.

The reservoir of Taldykol has been processed with L1 algorithm implementing Gao et al. 2019 as well as L2 processor and the results are shown in Figure 16 . The root mean square error is of 23 cm for 46 dates and which is mainly due to the date of 11/03/2017 as show in Figure 16. Considering we don't have in-situ data to validate, we estimated that the difference of time processing for large scale between L2 and L1 and the measure of the error were not justifying processing the whole areas of interest with L1 algorithm. Based on the same obervation, including Cryosat-2 mission was also discarded.

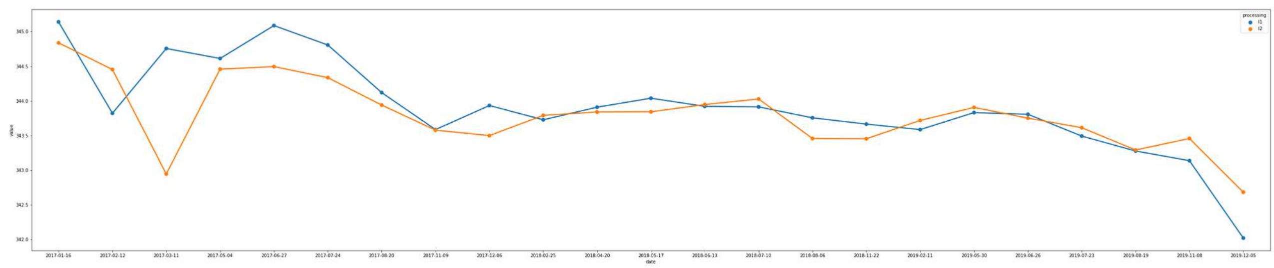


Figure 16. Water level time serie for Taldykol with L1 algorithm Gao et al. 2019 and L2 processor.

3.2.2.2 *Large scale processing*

Processing all the areas of interest, from the period of 2017-01-01 to 2020-02-01 led to:

- **373 virtual stations** with available water level time series (at least one water level value inferred during the period)
- **146 filtered virtual stations** (i.e.) with water level time series composed of *more than 10 water level values.*
    - **119 filtered virtual stations** in **Ishim** river basin
    - **38 filtered virtual stations** in **Nura** river basin
        - **8 filtered virtual stations** in the **Intumak-Sumarkand**
        - reservoir.

Water level time series with *more than 50 water level values* have been analysed to understand why the corresponding virtual stations were having so many available dates. A total of **10 virtual stations** has been found in the **Ishim** river basin and 4 in the **Nura** river basin. The analysis of the time series extracted for these virtual stations shows that this large amount of values is obtained as they correspond to the crossing of two different types of missions. Figure 17 shows the time serie for water level of one of the virtual stations (S3A based) displayed at each location (Ishim river close to Viktorovka and lake Aydabul), but the time serie obtained for the other virtual station (S3B based) was checked to be identical. Indeed, these two virtual stations almost completely overlap, hence a high number of available data points. One point from Jason 2 is available, because Jason 2 mission has a very high spatial but low temporal resolution for the period concerned as specified earlier.

Figure 17. Virtual stations and corresponding water level time series in Ishim river basin. S3B in yellow and S3A in orange in the map. Unit: meters. Confidence interval when several missions available per day in light blue. (Top) Ishim river close to Viktorovka, (bottom) lake Aydabul.

Virtual stations from Jason nominal tracks are presented in Figure 18, in Zhaltyr lake and Rechnoye lake. The variation is less than one meter for Zhaltyr lake which could be explained by the track of the satellite being very close to the border of the lake but insitu would provide more information.

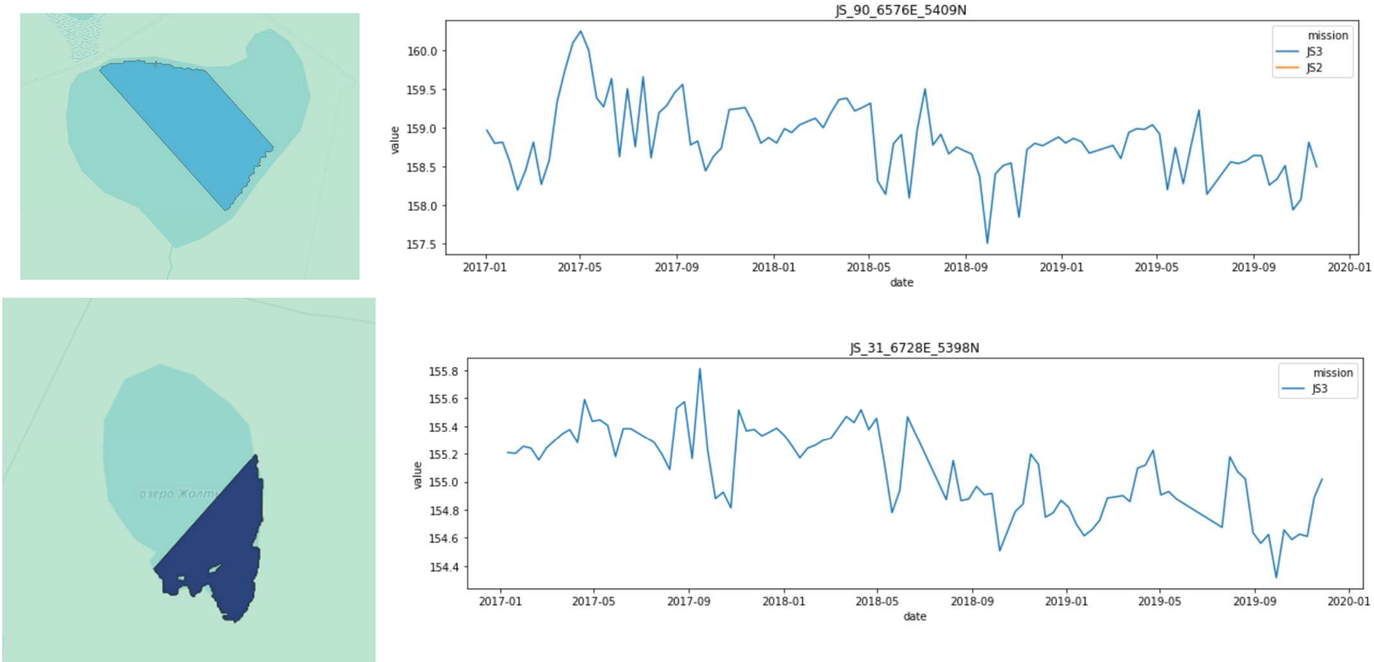
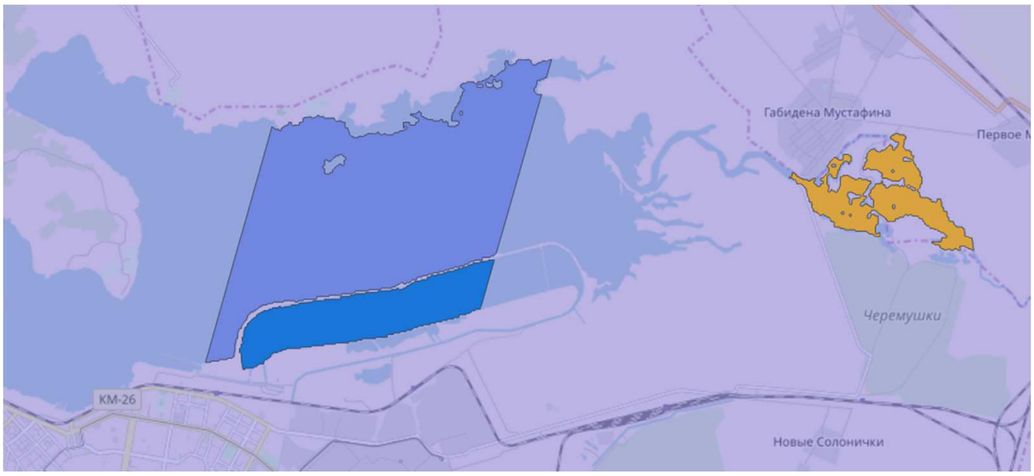


Figure 18. Virtual stations and corresponding water level time series in Ishim river basin for Jason missions. Unit: meters. Confidence interval when several missions available per day in light blue. (Top) Rechnoye lake, (bottom) Zhaltyr lake.

The 8 filtered virtual stations analysis within Intumak-Samarkand revealed that two of them were identical due to the fact they are right at the centre of the crossing of two S3A tracks from different relative orbits.

Therefore, 7 filtered virtual stations are within this region of special interest. The Samarkanskoe reservoir is particularly interesting as there are three different virtual stations close by as shown in Figure 19. Trends range are coherent for the three virtual stations, but we can see that the two located on the relative orbit 319 and which belongs to the bigger reservoir (S3B_319_7303E_5008N and S3B_319_7304E_501N) seem to be more impacted by variations. These two virtual stations are somehow connected and could be considered as one unique virtual station, so this is not surprising.



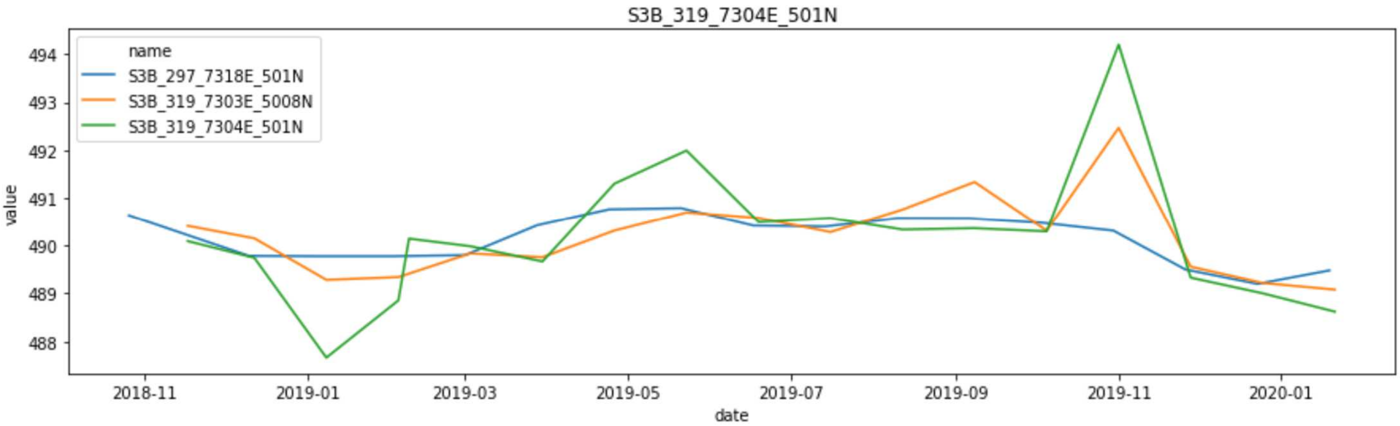


Figure 19- Virtual stations and corresponding water level time series for Samarkanskoe reservoir. Unit: meters. In the map, S3B_319_7304E_501N is in light blue, S3B_319_7303E_5008N is in darker blue and S3B_297_7318E_501N in orange.

All the **146 water level time series from filtered virtual stations** have been analysed and around 83% of them have standard deviations of less than 2 m and 70% of them have less than 30 values. Scatter plot of the number of values available versus the standard deviation of each time series is shown in Figure 20, and it reveals that virtual stations with high standard deviation within the corresponding water level time series (large variations) do not really correlate with the number of dates which could be the reason of a complex geometry. We then analysed the virtual stations with time series having standard deviation greater than 10m and 10 of them have been found. Imagery from Google earth history and information online have been tried to be browsed to understand the reasons of these large variations.

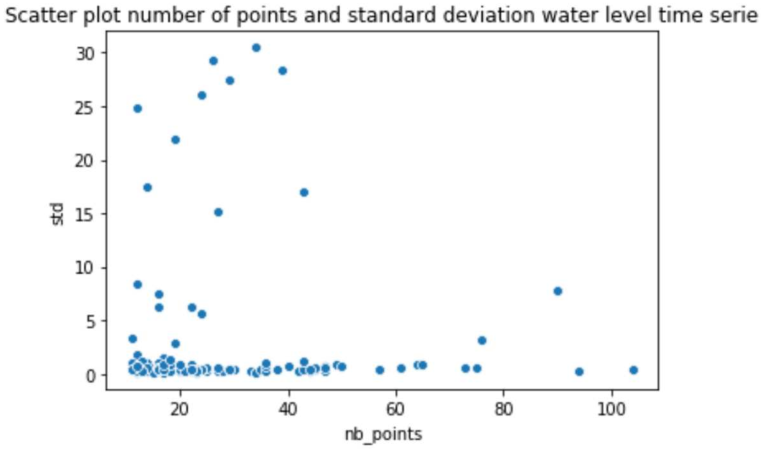


Figure 20 Scatter plot water level time series standard deviation versus number of values available for each virtual station.

Tuzkol Lake, located in the east of Almaty region (1950 meters above sea level), is the saltiest mountain lake in Kazakhstan and it appears that its salinity varies greatly across the season, reaching the salinity of the dead sea in Israel. The geologic formation of this lake could then explain the large variations which are shown in Figure 21 but this would need to be confirmed with beneficiaries and in-situ measurements.

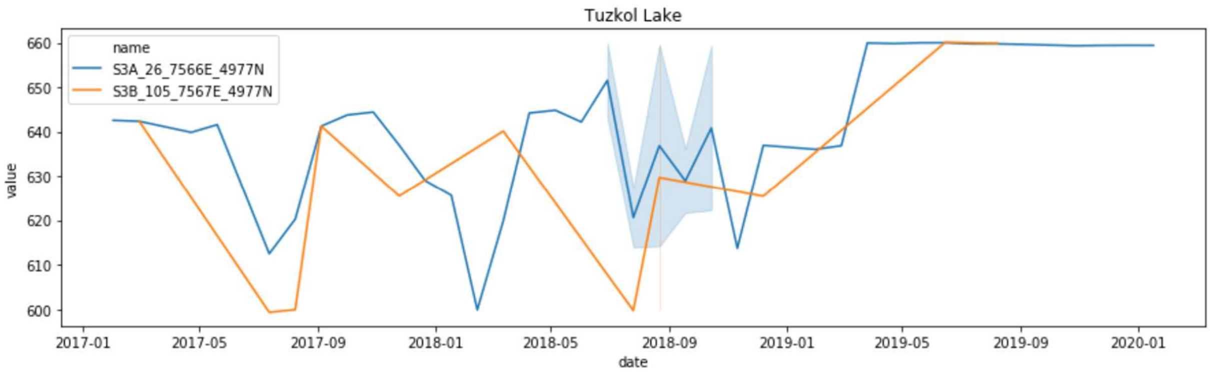


Figure 21 - Water level time series for Tuzkol lake . Unit: meters. Confidence interval when several missions available per day in light blue

In Figure 22, the analysis of the water level time serie from Karasevos lake discloses a large seasonal variation of almost 60 m. Google earth imagery from 4 years of difference were found, but before the period of interest. However, based on evidence, the Karasevos lake exhibits a large variation which might explain the observed variation. The range of 60 m happens to be extremely large, hence the possibility that the altimeter pulses hit vegetation on the ground. Further validation with in-situ measurements and observations should shed light on this preliminary explanation.

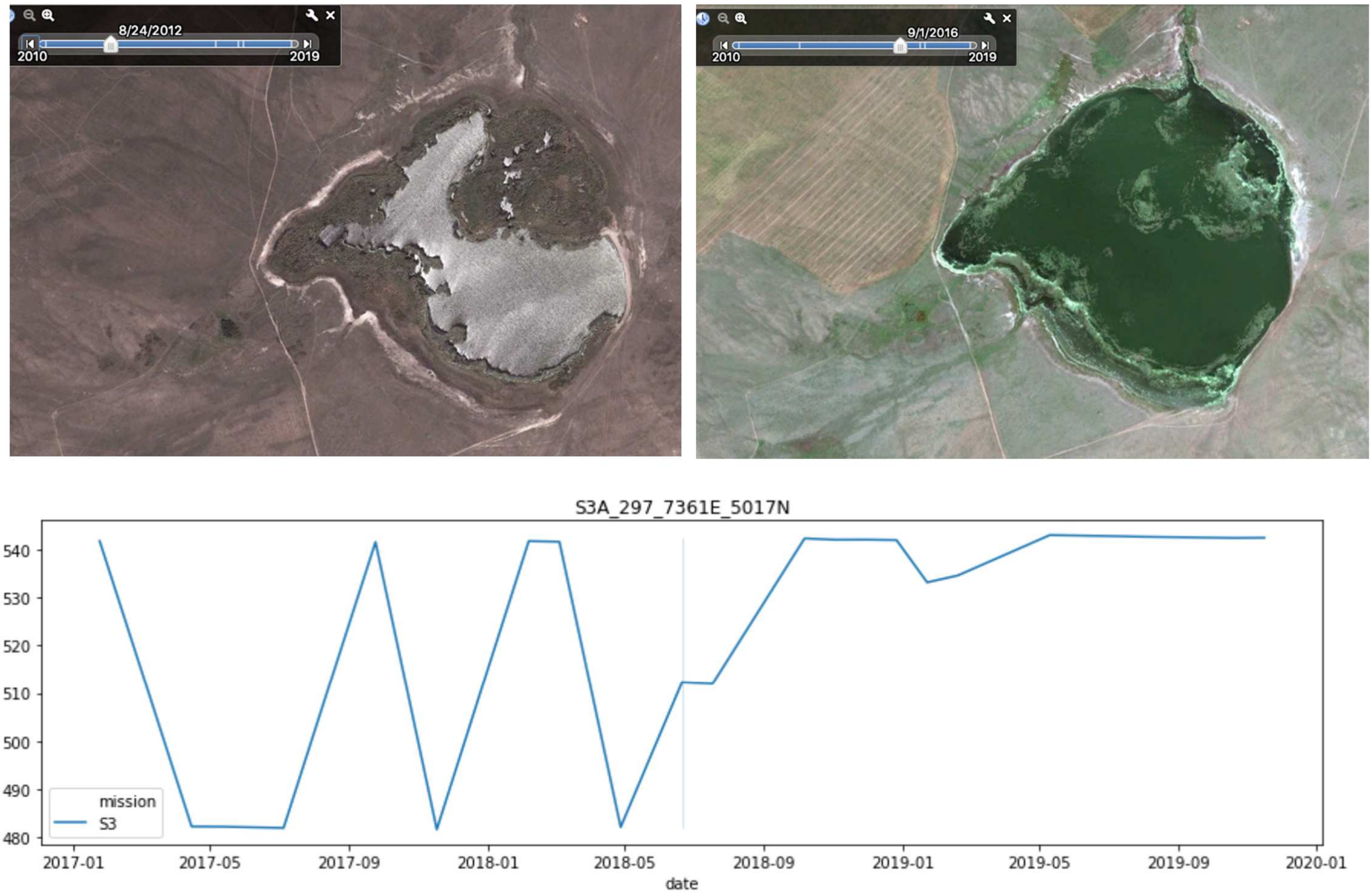
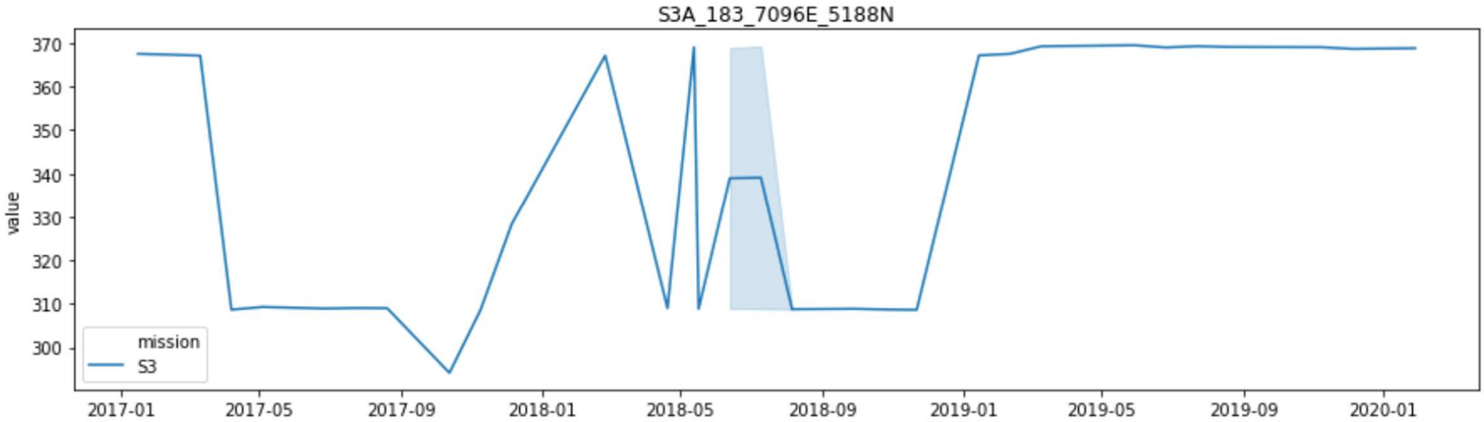


Figure 22 - Karasevos lake. (Top) imagery from August 2012 left and September 2016 on the right. (Bottom) water level time serie.

Finally, water bodies close by the villages of Enbek and Puchalskoe (seeFigure 23) respectively also uncovered large variations (70 m) and sudden increase in fall 2019 which could be explained by a flood. These two locations should also be examined with the help of beneficiaries so that variations can be justified.



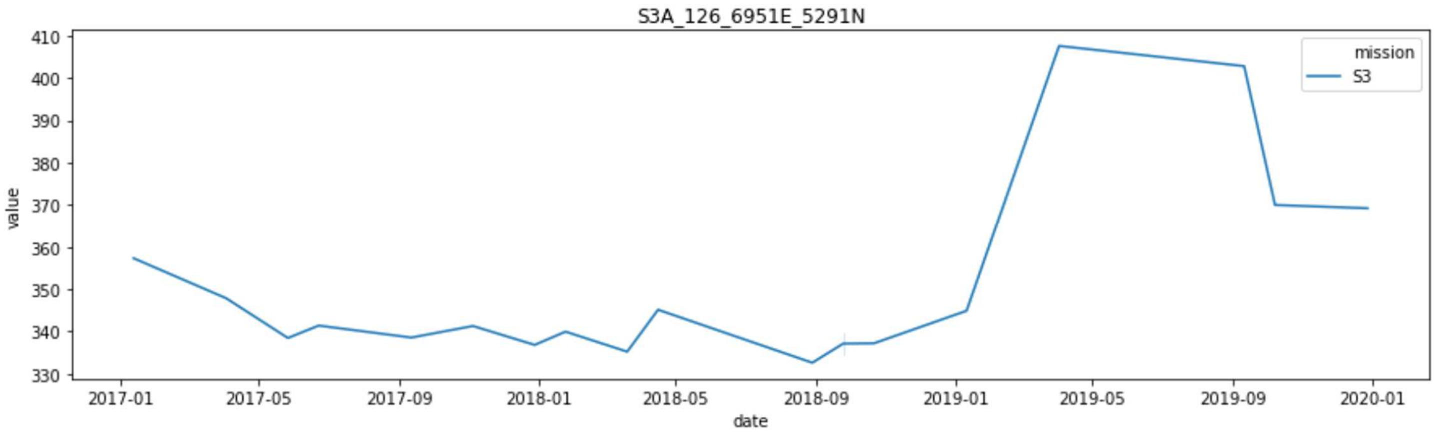


Figure 23 - Water level time series for (Top) Enbek and (Bottom) Puchalskoe

3.2.3 Usage, Limitations and Constraints

A total of **373 virtual stations** have water level values for the period of 2017-2020. However, some of the virtual stations, at the crossing between two satellite tracks, overlap almost perfectly and could be fused into a unique one. These virtual stations could be validated by local measurements and beneficiaries.

Water level values are provided as absolute values with reference to the geoid EGM2008 but if the end-users want to use them, they need to be aware of this information. Moreover, each of the mission considered (S3A, S3B, JS2 and JS3) disclose a bias as two different tracks intersecting a unique water body might not be co-located.

Virtual stations produced on demand are based on JRC Surface Water Explorer dataset by extracting areas covered by permanent water. This condition is restrictive as the masks can sometimes be very narrow and not so many altimetry points can be taken into account which explains why there are **146 filtered virtual stations** (i.e.) with water level time series composed of *more than 10 water level values.*

As no in-situ data are yet made available for the region concerned and the two closest stations available in public datasets (Hydroweb and Dahiti) are out of the region of interest, assessing the exact accuracy of our algorithms in this region of the world is still a challenge. However, the preliminary analysis of the results presented in the previous section should help on targeting a first set of specific areas to investigate water level time series.

A subset of 11 water level time series are provided as a data package in this study, with 7 of them located in the Intumak-Samarkand reservoir. However, as detailed in above, up to **373 virtual stations** have water level time series across the whole area of interest and could be of special interest for the beneficiaries as shown in the following Figure 24.

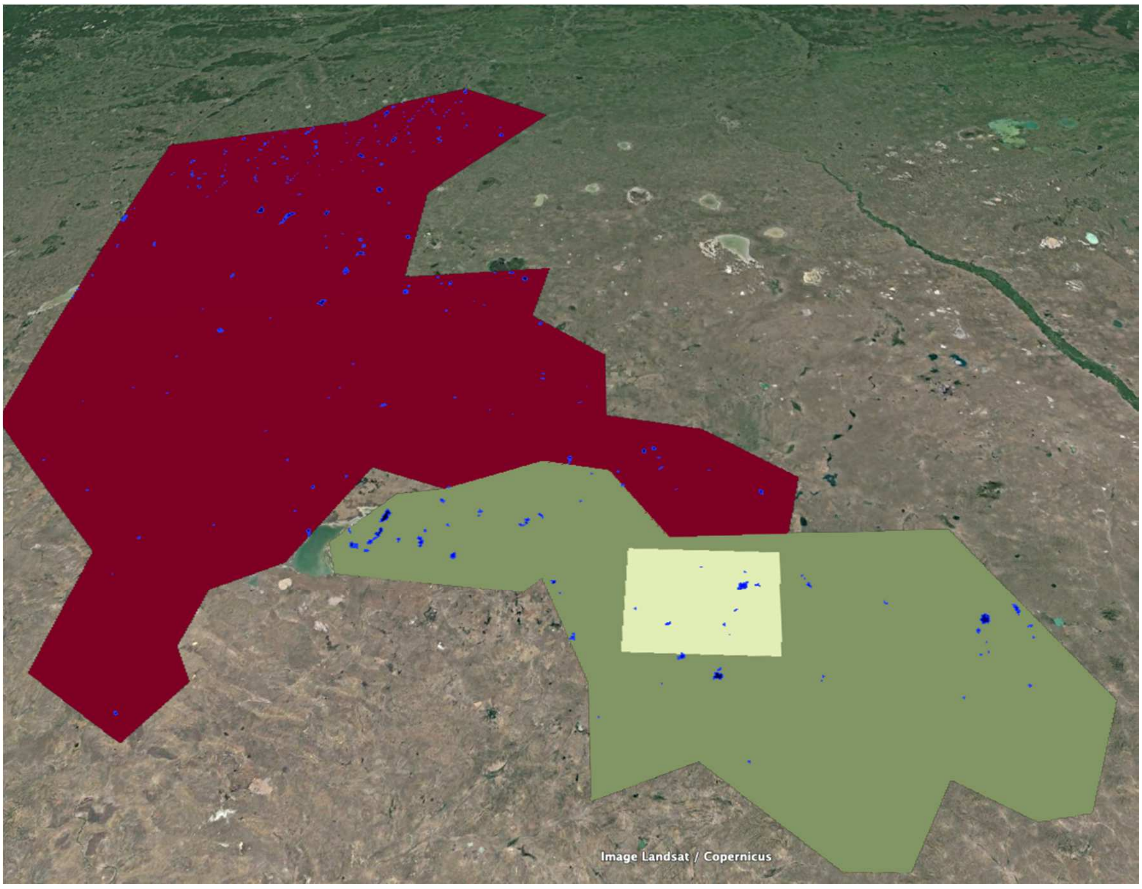


Figure 24. Virtual stations with water level time series for the period 2017-2020 in the areas of interest of EO-clinic in Kazakhstan.

The data package handed in is composed of:

- A shapefile: *virtual-stations-with-ts.shp* with the **373 virtual stations** geometries with water level values (see Figure 24).
- A .csv: *idmapping.csv* containing the mapping between uuid and name of 11 selected the virtual stations.
- A folder *time-series* with 11 subfolders named by uuid which contain a *waterlevel.csv* file for each virtual station.

3.3 Service 3: Estimates of Total Water Volumes

This service combines Service 1 with Service 2 (water contours and levels) to provide estimates of changes in water volumes for a selection of permanent water bodies. The preliminary results for Taldykol reservoir and Samarkandskoe are shown below. Figure 25 show the temporal development curves of water levels and associated change in water storage over the 2017 to 2018 time-period for the Taldykol reservoir. From the timeseries we can see that maximum water extent is at the very beginning of the period (cf. May 2017) whereas minimum water extent occurs during August the following year. The maximum and minimum water extent maps is shown in Figure 26 with corresponding Sentinel-2 images as background.

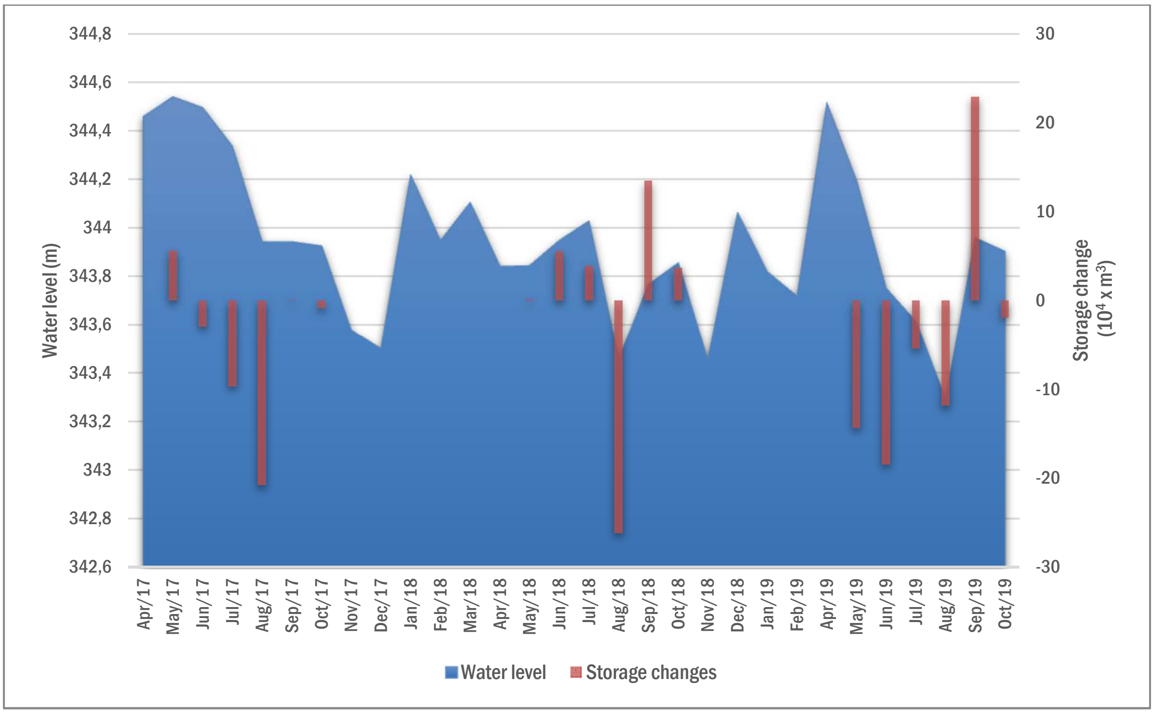


Figure 25. Water level and storage changes for the Taldykol reservoir just southwest of the capital Nur-Sultan.

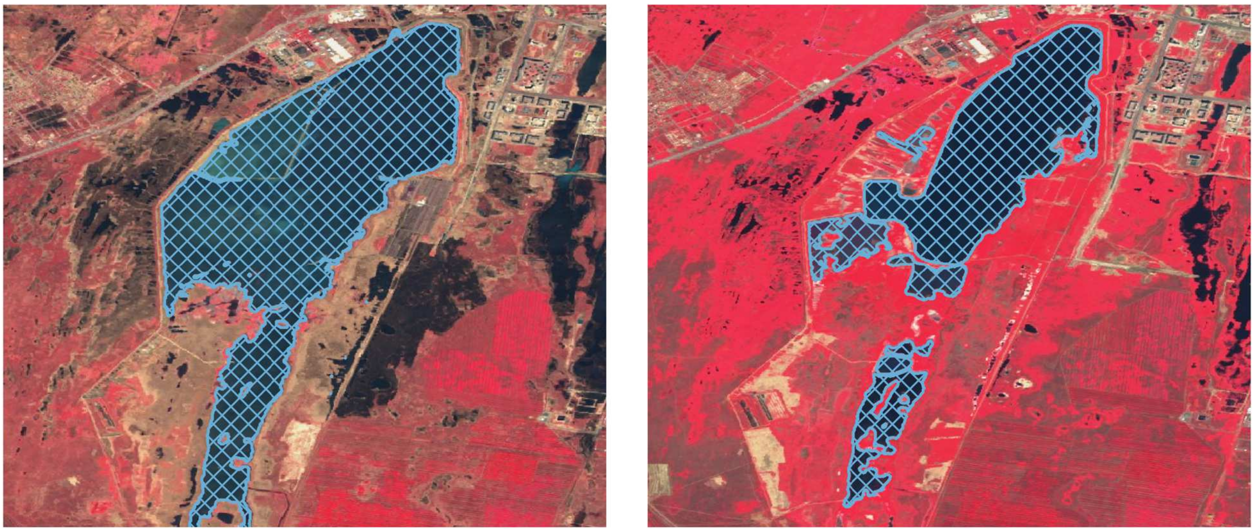


Figure 26. Maximum water extent (May-2017) versus minimum water extent (August-2018) at the Taldokyl reservoir just southwest of Nur Sultan. Background images are from Sentinel-2 acquired on 18. May 2017 and 18. August 2018 respectively.

The Samarkandskoe represent a different use case. From the water level profile we get that similar to Taldokyl the max water level (considering the ice free period only) is in May and with minimum water levels occurring in October (Figure 27).

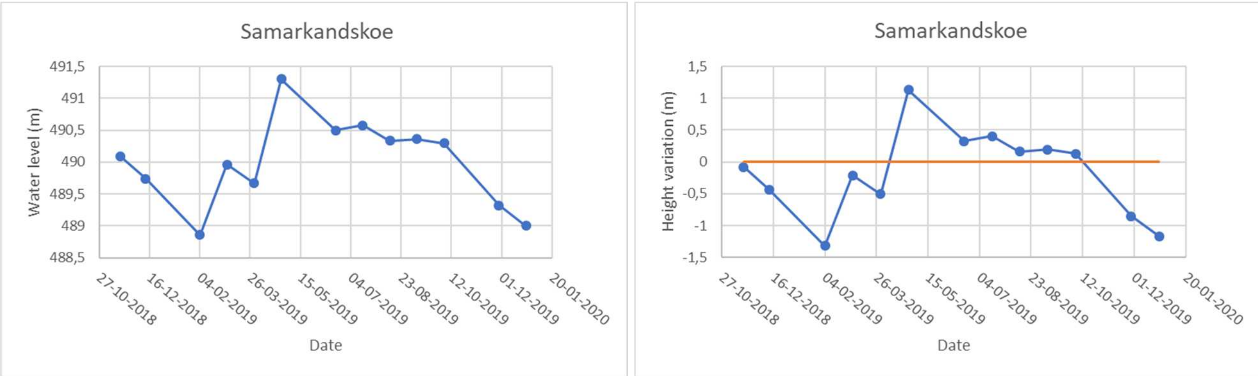


Figure 27. Water level time series (left) and height variation from normal operating levels[1] (right) for the Samarkandskoe reservoir.

Yet, the surface water extent over Samarkandskoe shows little variation (Figure 28) and the reservoir water storage changes is therefore almost entirely given by the change in water height and possible indicating a very steep bathymetry of the reservoir. The surface water area in May 2019 is 61.9 km^2 and 61,1 km^2 in October 2019. The corresponding water levels are 491.3 m and 490.3 m, which leaves us with a water storage change of $412x10^4$ m^3 between minimum and maximum level.

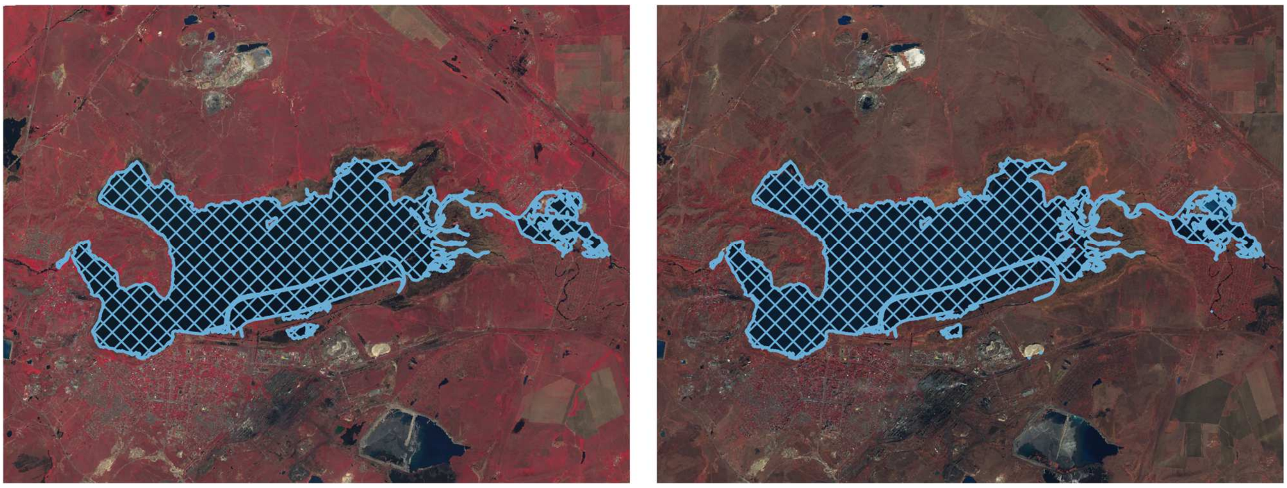


Figure 28. Water extent at time of maximum water level (May-2019) versus water extent at minimum water level (October-2019) at the Samarkandskoe reservoir. Background images are from Sentinel-2 acquired on 12. May 2019 and 7. October 2018 respectively.

Apart from Taldokyl og Samarkandskoe there is an additional 4 reservoirs (id: 71b,52b,92f and db2) in the Intumak and Samarkand reservoir area (green polygon) for which we have simultaneous altimetry and water extent observations (cf.).

[1] From: http://www.cawater-info.net/bk/1-1-1-1-3-kz_e.htm

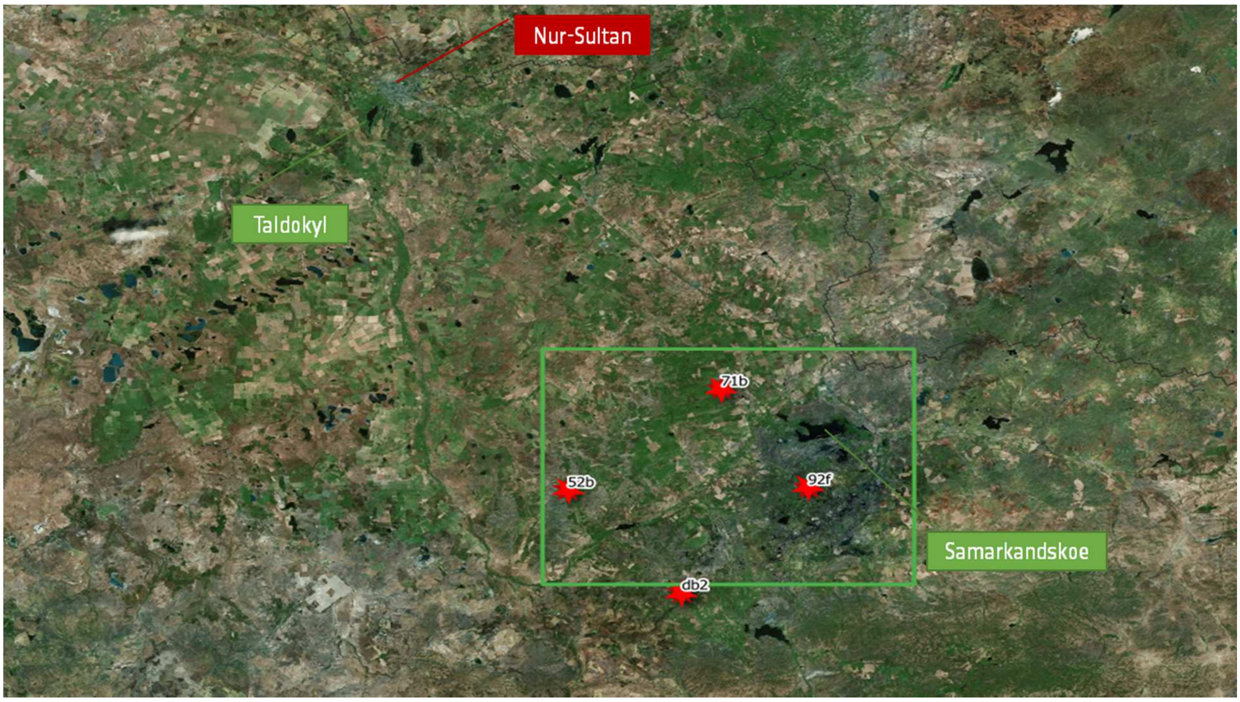


Figure 29. Location map of reservoirs for which water storage changes has been estimated from simultaneous altimetry and water extent observations.

The results from those additional reservoirs are presented in Figure 30.

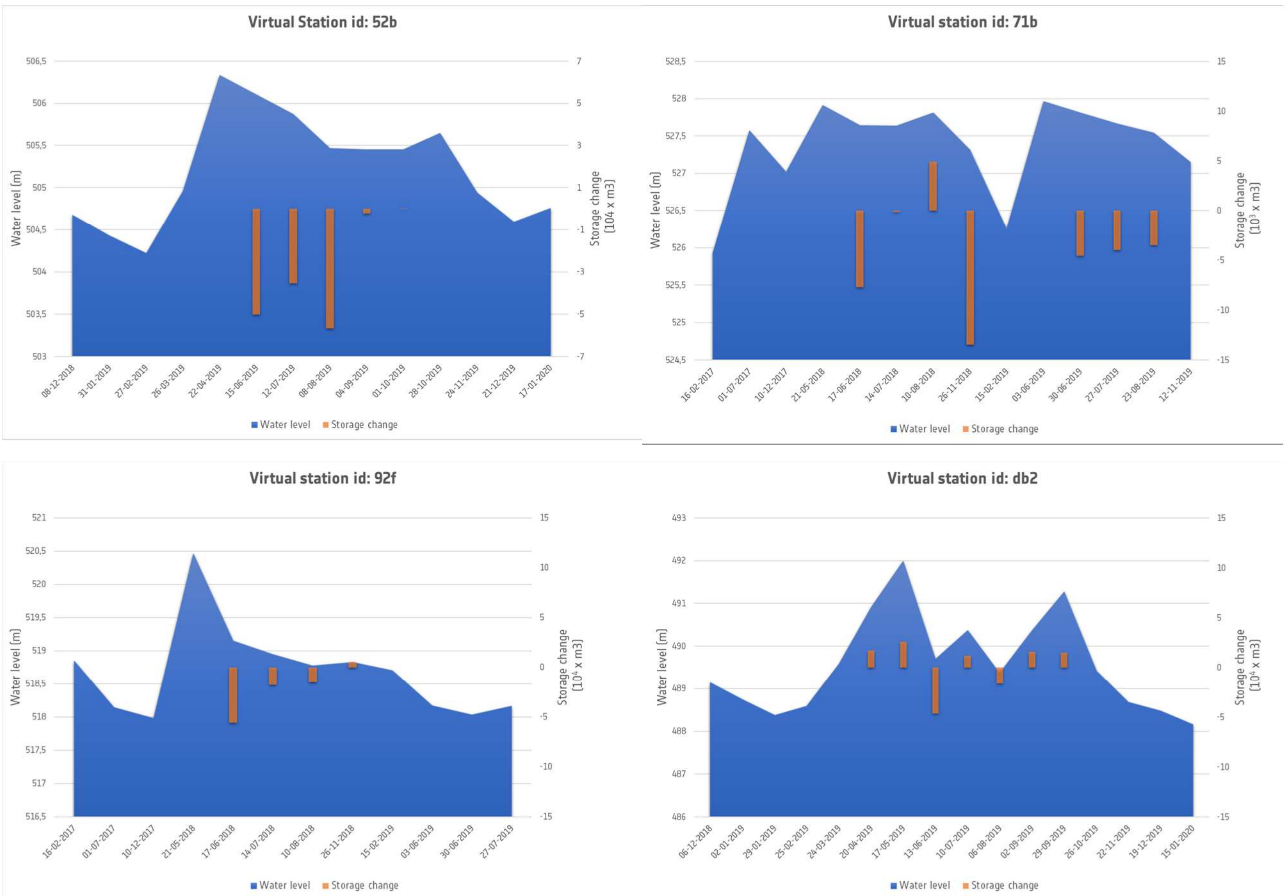


Figure 30. Water level and storage changes for reservoirs in the Intumak and Samarkand reservoir area.

3.3.1 Specifications

Technical specifications for the water volume estimations is summarized below.

EO input data: Sentinel-1, Sentinel-2, Sentinel-3

Other input data: Surface water extent maps (service 1) and water level time series (service 2)

Method: Lake/Reservoir water storage changes is estimated using the following equation:

$$S = 1/3\ (H_2 - H_1)\ (A_1 + A_2 + \sqrt{(A_1 + A_2\ )})$$

where, S is the storage change; H_2, H_1 and A_2, A_1 are lake levels and areal extents at different dates, respectively

Output indicators: Time series of changes in water storage

Units: m^3

Spatial resolution: Individual reservoirs

Temporal resolution: Monthly, 2017-2019

Delivery format: Ascii (.txt), Excel

3.3.2 Quality Control and Validation

Please refer to section 3.1.2 and 3.2.2. In addition all individually water extent polygons were checked visually for consistency before the surface water area was calculated and used in the calculations.

3.3.3 Usage, Limitations and Constraints

Monitoring of water levels in lakes and reservoirs can be used to assess changes in water reservoir storage. By example the high-water levels experienced in the Taldykol reservoir in May 2017 coincides with intense floods experienced in northern and central Kazakhstan in April 2017 and following heavy rains. Ideally, one would be able to establish a robust stage-area curve so storage change estimation could be estimated if just one of the unknowns are known (i.e. either surface water area or surface water height) and in which case continued monitoring of either water levels or surface water extent could provide an early indication of a potential flooding situation. For Taldokyl and Samarkandskoe such a clear relationship does not exist, and it remain to be seen if and for how many reservoirs this may apply within the region of interest. An alternative, usage of water levels to support flood mitigation would be to look at virtual stations at river crossings upstream exposed areas and potentially combined the altimetry-based water levels with a hydrological model for flood forecasting.

3.4 Methodology clarification

The altimetry method used to derive the water level time series has been largely and extensively validated and show very consistent performances in different context. Performances can vary in very complex mountainous terrain, due to the lack of altimetry data in those areas, affecting mainly the frequency of the observations. In terms of known performance of values, from the existing numerous references: spontaneous absolute values from altimetry can differ from in-situ stations from 0.16 to 0.9 meters (greatly depending on the actual track location on the water body and the number of values that fall on the water surface). Therefore, we are confident of the performance in Kazakhstan, and consider that in-situ validation is not necessary.

Yet, in case the client can provide access to existing water level observations (measured in-situ) for any water body, the consultant will evidently conduct the match up analysis between the in-situ and the altimetry-based water levels for the given water body.

The water level observations obtained from satellite altimetry at individual virtual stations are measured with respect the mean sea level (MSL). When shown as relative variations, these are represented against a defined reference water level (e.g. the observed mean water level over a given time period). While using the average of the time series value for showing water level variations is generally recognized as being state of the art, it is not the ideal scenario when the input time series is short and therefore potentially not representative for the long time average water level of a particular water body. In Kazakhstan most of the obtained altimetry water level timeseries only spans one or two years and this is the reason why the depiction of relative heights variations needs to be treated cautiously. As the time series is built up and we get access to more data, then the average value will become more representative and the observed height variations much more relevant as water status indicator.

In the work order for EO-Clinic RFP003 water level fluctuations are depicted both in absolute terms (relative to MSL) and as relative height variations against the observed mean water level. The example for Taldokyl is shown below in Figure 31 and Figure 32, while the results for the other water bodies is found in the attached Excel sheet.

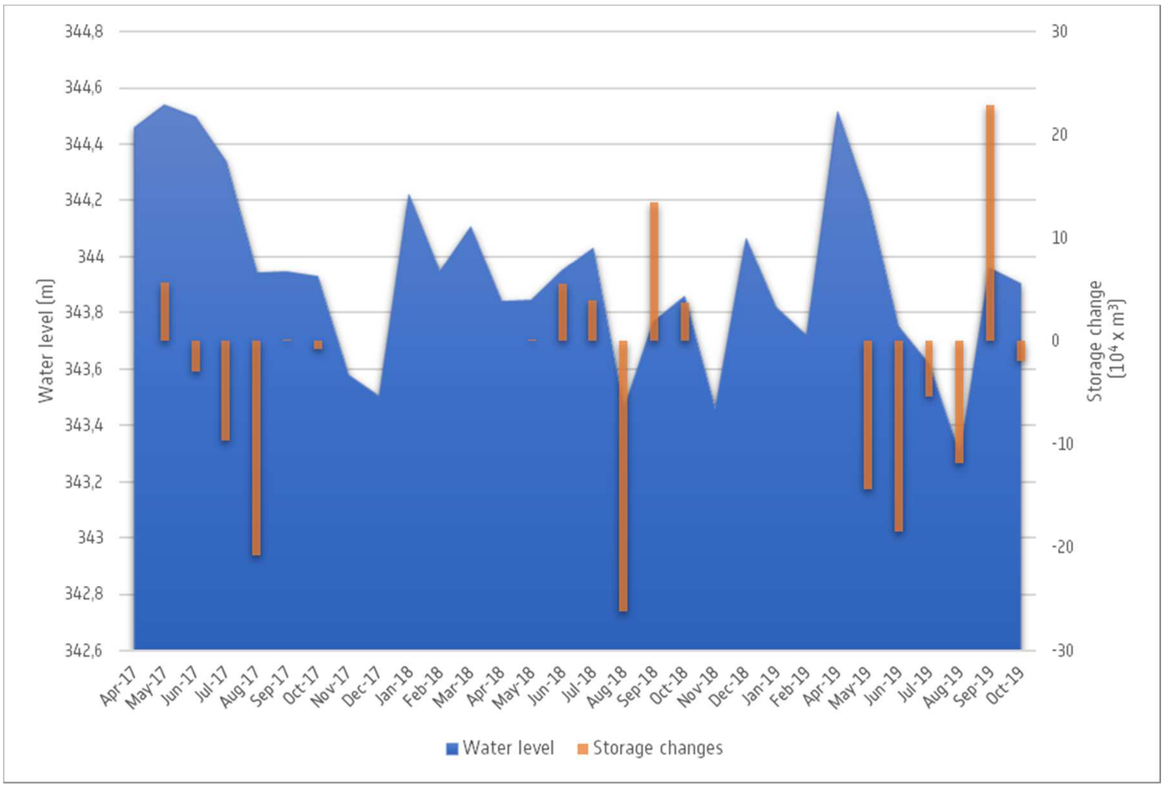


Figure 31 Absolute water level fluctuations and associated water storage changes for Taldokyl reservoir

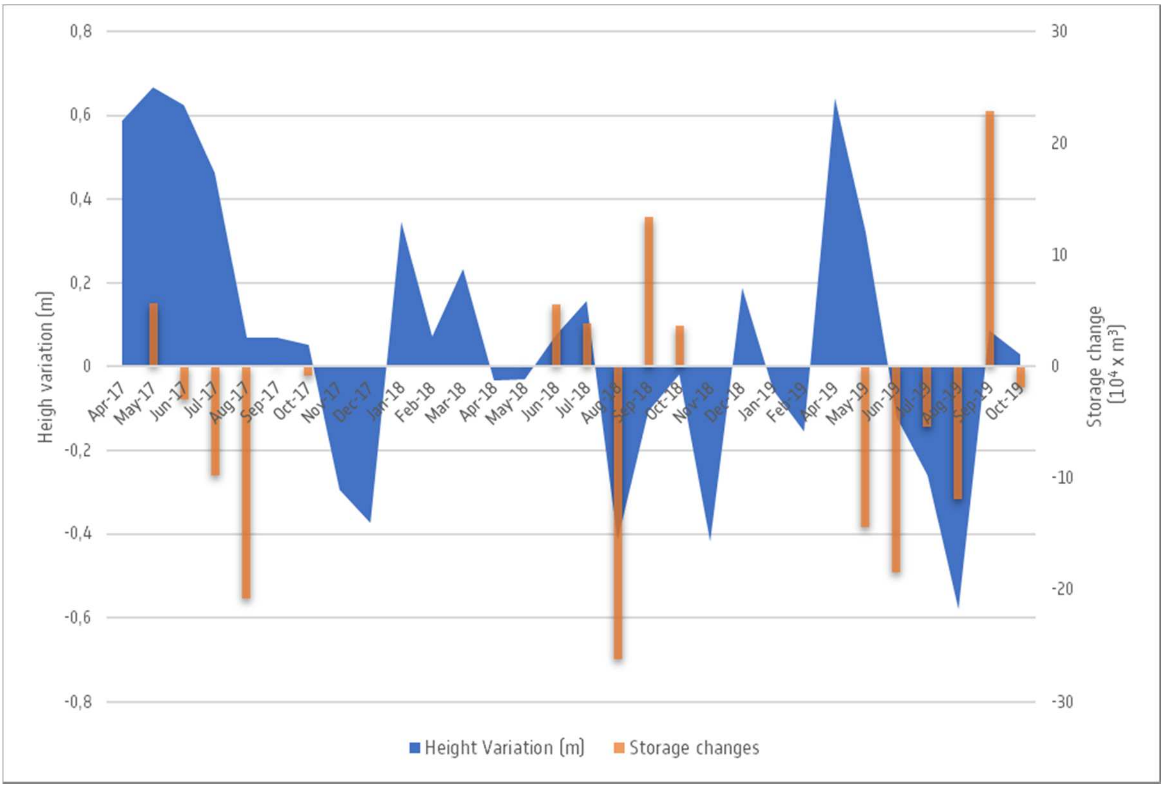


Figure 32 Variations in relative water heights shown along with changes in water storage

3.5 WEBGIS publication

As a final deliverable a web viewer has been delivered for easy display of the maps and water level time series produced under this procurement (cf. Figure 33).

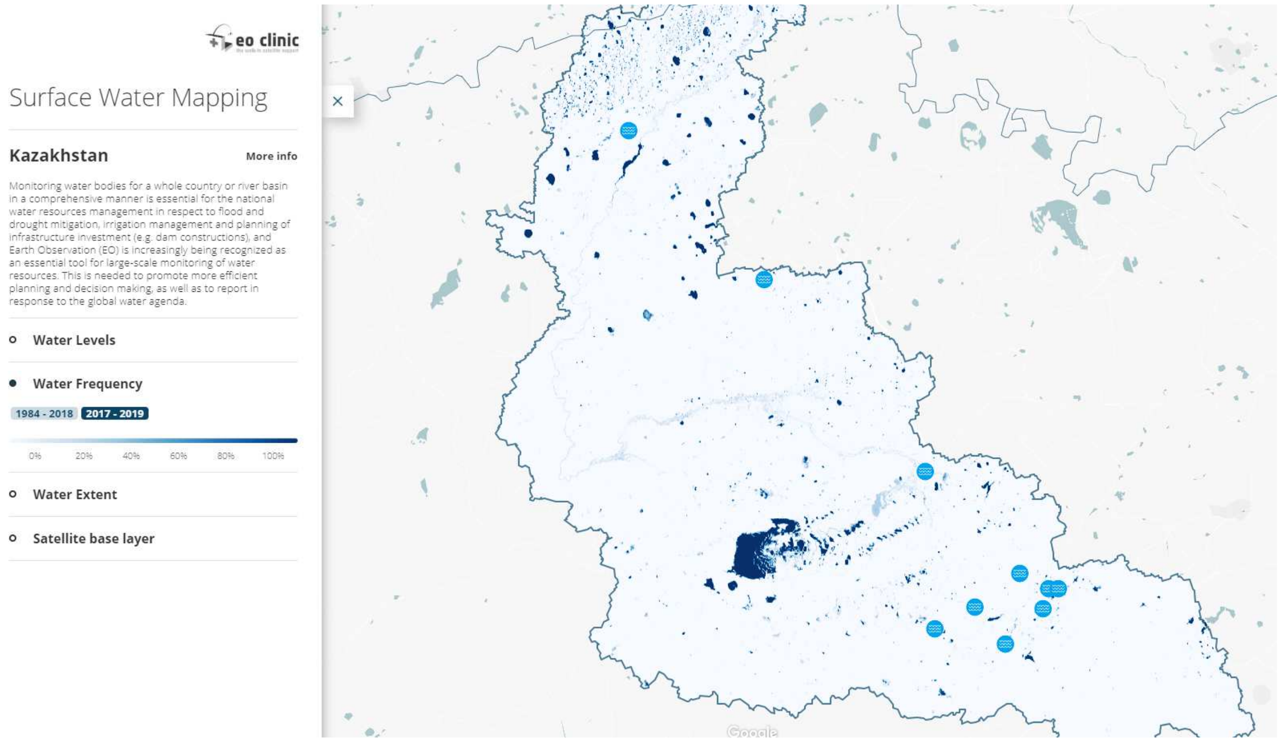


Figure 33. Screen dump of the web viewer for publishing the results.

The web viewer can be accessed by clicking the following link: http://labs.dhi-gras.com/eo-clinic/

4 Requirements for EO service continuation

The surface water monitoring information produced under this procurement can be performed by consulting best practice guidelines and by using free data (cf. Annex A) and open source tools. The real challenge therefore is not the mapping itself but rather the scaling and institutionalization of the mapping. National scale surface water monitoring with Sentinel-1/Sentinel-2 imagery may involve processing of thousands of satellite acquisitions and terabytes of data. In such cases a conventional desktop environment may not suffice rather interested parties should explore cloud-based solutions where the raw satellite imagery is accessed via the internet and processing performed through a shared online computing infrastructure.

There are basically two models that can be followed if the Kazakhstan stakeholders wish to continue the EO services provided under this procurement. Either the services are continued through a service-level agreement with an EO service provider, or alternatively the stakeholders will make the necessary investment in upgrading human and infrastructure resources to ensure the services can be run by a mandated institute of their choice.

The estimated cost associated with either option, and as per demonstrated EO service is provided in the following sections.

4.1 Surface water extent monitoring

Service-level agreement

The following two option describe the continuation of the service ZRBMP.1 (Surface Water Monitoring) as is, that is, through the current service provider using identical or very similar means of service delivery.

Service	Description	Specifications	Cost
Surface Water Monitoring	Monitoring of national surface water resources based on Sentinel 1 (SAR) & 2 (Optical) image interpretation.	Ishim and Nura basin (Kazaksthan part) **Resolution**: 10m • Monthly water body masks • water frequency maps for past 12 months • statistical information on individual water body level.	18.000 € / year

Technology transfer

The table below summarizes various solutions and estimated cost for technical assistance for installing national capacity for operational surface water mapping

Software solution	Advantages	Limitations	Cost
1. eo-learn eo-learn.readthedocs.io/en/stable/	Open-source solution Easy to setup operational processing chain Quick and efficient (processes only the required data) Can combine optical and SAR data	Data access is not free Depends on https://sentinel-hub.com/ service Embedded cloud mask not including the shadow Data pre-processing can be customized with additional development cost	Data – 500 EURO / year / 100.000 km² (assuming both optical and SAR data) Development, deployment, training and support costs – 2-3 man months
2. Google Earth Engine earthengine.google.com/	Multiple and planetary-scale satellite data archives Relatively simple implementation Fast processing Can combine optical and SAR data	Subject to Google conditions which can change with short notice Data and processing are run fully in the cloud (no local ownership) Limited developing and implementing of non-GEE (advanced) algorithms	Deployment, training and support costs – 2-3 man months
3. Customized solution	Full ownership of code. Delivers analysis ready data which can be used for surface water mapping but also for many other purposes and serving many different stakeholders. Can combine optical and SAR data Most robust as cloud masking, atmospheric correction, machine-learning model etc. can be optimized	Higher development cost Might require more technical knowledge and skills.	Development, deployment, training and support costs – 3-5 man months, more if GUI is to be developed

Surface water monitoring can be implemented on either local or on cloud infrastructure. Users interested in services at national/regional scale is advised to use a cloud-based solution where the raw satellite imagery is accessed via the internet and processing performed through a shared online computing infrastructure.

The estimated cloud infrastructure cost is provided in Annex 2. Note: Google Earth Engine is run fully in the cloud and is currently free, but this could change at short notice.

Solution 1 and 3 can be run either locally or on cloud infrastructure. Rough cost estimate for the cloud infrastructure is presented below (based on e.g. DIAS). Google Earth Engine is run fully in the cloud and is currently free, but this could change at short notice.

Table 3. Cloud-infrastructure cost

Hardware	Description	Cost (Euro/month)	Cost (Euro/year)
Processor	Min. 8 cores and 64 GB RAM	600-800	6600-8000
Storage	Final and temporary outputs. Cost is per 10 TB (i.e. the Sen2Agri requirement for 100 000 km^2). The cost is likely to be less for the other solutions if only optical data is used but more if optical and SAR data are combined).	600 (HDD) - 2000 (SSD)	600 (HDD) - 2000 (SSD)
Bandwidth and other costs	Data transfer to and from the machine and miscellaneous costs	1500	1500
Total		2700-4300	8700-11500

Annual cloud infrastructure costs for running the demonstrated services will vary depending on the required server time. If a full operational system is required prices will be close to 12K Euro per year, but less if the production and outputs is only required in batches e.g. acquiring the infrastructure in two months to produce the surface water masks for previous years.

4.2 Water levels

Service-level agreement

The actual implementation and cost of the water level service based on space radar altimeters can take various forms.

Solution 1: represent the basic consultancy required to setup an integration of the baseline dataset of water level (WL) timeseries over the identified virtual stations in this study (2017-2020), filtered (146) and /or non-filtered (373), into a national water resource monitoring (WRM) system.

Solution 2: represent the upgraded consultancy required to setup an integration of the baseline dataset OF WL timeseries over the identified virtual stations in this study (2017-2020), filtered (146) and /or non-filtered (373), into a national water resource information system AND update the dataset once a month/a year.

Solution 3: represent the expert consultancy of integrating the service of WL processing into a relevant DIAS which would allow the user to obtain:

- near real time WL timeseries automatically over the identified virtual stations in this study, filtered (146) and /or non-filtered (373) .
- on demand processing to retrieve WL timeseries on any water body located on a altimeter track.

In this solution, training of users should be considered.

Solution	Limitations	Cost
1. **Visualize:** Integration of the baseline dataset (2017-2020 for 300+ virtual stations) into your WRM system with embedded visualization.	Availability of the time series until February 2020.	8.700€ euros.
2. **Monitor:** Assisted monitoring per month/year of the baseline dataset (since 2017 for 300+ virtual stations) into your WRM system with embedded visualization.	Availability of the time series once a year/month.	17.400€ the first year and 8.700€ consecutive years.
3. **Expertise:** Capacity building and training to obtain near real time update of the baseline dataset (since 2017 for 300+ virtual stations) with embedded visualization in a DIAS.	Long time of development.	Prices depending on the chosen DIAS: *With H-TEP DIAS* • Setup and subscription DIAS: - First year: 7.500€. - Consecutive years: 6.500€. • Integration of the water level service: - First year: 7.000€. - Consecutive years: 0€. • Computational and service cost: 17.500€/year. • Training of the users: - First year: 18.000€+ travel costs - Consecutive years: 3.000€ (online). Total:

		- First year: 50.000€. - Consecutive years: 27.000€. *With Wekeo DIAS* • Setup DIAS and Integration of the water level service: - First year: 14.500€. - Consecutive years: 0€. • Computational and service cost per year: 11500€/year. • Training of the users: - First year: 18000€+ travel costs - Consecutive years: 3000€ (online). Total: - First year: 44.000€. - Consecutive years: 14.500€.

ANNEX A: EO DATA ACCESS AND LICENSE CONDITIONS

The execution of the current procurement is based entirely on free and open data from the European Copernicus program in combination with data from contributing mission (e.g. JASON and Landsat). The below table summarize the used EO data their main access points and their license conditions.

Sensor	Access	License conditions
Sentinel-1 (2017-2019)	Copernicus Services Data Hub (https://cophub.copernicus.eu/)	None (free and open data)
Sentinel-2 (2017-2019)	Copernicus Services Data Hub (https://cophub.copernicus.eu/)	None (free and open data)
Landsat 8 (2013-2016)	EarthExplorer (https://earthexplorer.usgs.gov/)	None (free and open data)
Sentinel-3 (2016-2020)	Copernicus Services Data Hub (https://scihub.copernicus.eu/)	None (free and open data)
Jason-2 and 3 (2016-2020)	NOAA NASA (https://www.nodc.noaa.gov/Satellite-Data/jason/)	None (free and open data)
Cryosat-2 (2016-2020)	ESA (https://science-pds.cryosat.esa.int/)	None (free and open data)

APPENDIX B: TEMPLATE OF A BIBLIOGRAPHY

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