Geneva, 31 May 2023

Pilot study on the potential of aerial photographs and other remote sensing methods to detect dry watercourse sections during drought periods – Final report

1. Background

Due to climate change, an increase in drought situations (duration and intensity) is expected for Switzerland. The hydrological scenarios indicate a significant decrease in summer runoff with a simultaneous increase in water demand, especially by agriculture. Therefore, drought events such as those in 2003, 2015 or 2018 and water scarcity must be increasingly expected in the future. Within the framework of a project on drought information initiated by the FOEN, methods are to be tested to improve information on water resources before, during and after droughts.

In this context, the potential of remote sensing data (aerial photographs, drone images, satellite images) also needs to be investigated. This is the main objective of the pilot study at hand. Such data could for example be used to detect, map, and inventory watercourse sections throughout Switzerland that are susceptible to drying out during drought periods. This can help to gain a comprehensive overview of where particularly vulnerable water bodies or regions are located and to what extent, for example, renaturation projects could be prioritized, or water use conflicts anticipated. Furthermore, such an overview might provide valuable information on representative sites for targeted monitoring. Lastly, such information could be made available as timely as possible during droughts.

The project deals with Priority III of the Research Concept Environment 2021-2024: Protection and Sustainable Use of Resources and Ecosystems in the Area of Water. The points 10.1.1 Impact of climate change on water bodies and water management and 10.1.3 Development of basic principles and methods for information on water consumption addressed.

2. Assignment, Description of Work Required and Deadlines

GRID-Geneva provides support to FOEN in relation to:

Activity 1: Literature review on techniques and current applications and their accuracy to detect dry watercourse sections during drought periods using (very-) high resolution aerial, drone, and satellite imagery.

Expected results: Identification of the candidate techniques to be tested, summary of the literature review and current applications (to be included in Activity 5), and accuracy assessment and validation applied in Activity 3-4.

Activity 2: Compilation of available imagery data (SWISSIMAGE as priority data set) with sufficiently high spatial resolution during drought events (e.g., 2003, 2011, 2015, and 2018) of potentially affected stream segments and creation of a reference dataset to compare dry vs. normal conditions.

Expected results: A compilation of available (very-) high images of affected rivers & a reference dataset for comparison with “normal” conditions. This will serve as the basis for the decision whether to proceed with activity 3.

Activity 3*[optional]: Development and implementation of a method for automated detection and visualization of dry water sections (in comparison to the reference data set)

Expected results: A first version of the algorithm is implemented on test areas + accuracy assessment and validation

Activity 4*[optional]: Evaluation of the results (for example in a "water body vulnerability map") and identification of the difficulties or the need for further research.
Expected results: Report on the evaluation of results; identification of challenges; definition of improvements

Activity 5: General assessment of the potential of aerial, drone, and satellite imagery for use during future drought events in Switzerland. Based on this, elaboration of a recommendation on how, where and when such remote sensing methods could be deployed in this context (incl. "cookbook recipe"/guidance for the use during drought periods).
Expected results: Final report with a general assessment of the tested methodology and literature review from Activity 1; set of recommendations; and cookbook to apply the methodology.

*[optional] *Activities 3 and 4 are listed as optional because they depend on the outcomes of previous activities. The decision whether these optional activities will be released will be taken by the FOEN project team after the evaluation of the outcomes of Activity 1 and 2.*

Timetable of the project:

Activity	From start of project	To
#1	M1 [Sept. 2022]	M2 [Oct. 2022]
#2	M2 [Oct. 2022]	M3 [Nov. 2022]
#3	M3 [Nov. 2022]	M5 [Jan. 2023]
#4	M6 [Feb. 2023]	M7 [Mar. 2023]
#5	M8 [Apr. 2023]	M9 [May. 2023]

3. Activities outcomes

NB: Specific reports for activity 1 and 2 can be found in annexes.
Activity 3 & 4 have been released because of the positive outcomes of Activity 1 & 2.

3.1 Activity 1

Outcomes of this activity have been presented in a previous report. As a reminder, it has been added under Annex 1.

3.2 Activity 2

Outcomes of this activity have been presented in a previous report. As a reminder, it has been added under Annex 2.

3.3 Activity 3

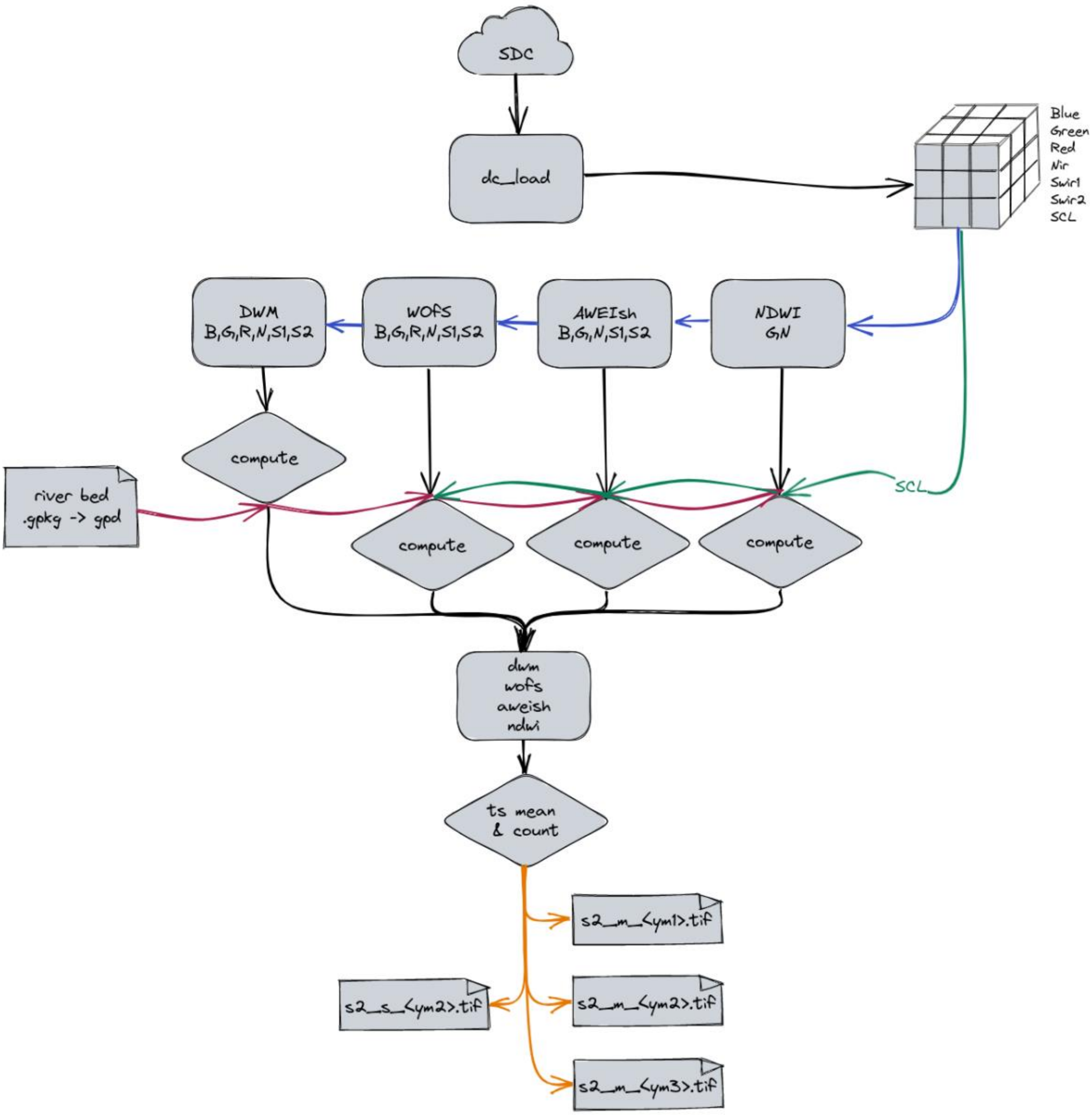
Development and implementation of a method for automated detection and visualization of dry water sections (in comparison to the reference data set).
Expected results: A first version of the algorithm is implemented on test areas + accuracy assessment and validation.

1. Sentinel-2 time series analysis

Based on the outcomes of activities 1 and 2, identified indices were computed for all Sentinel 2 and synthesized seasonally and monthly. Using the following parameters:

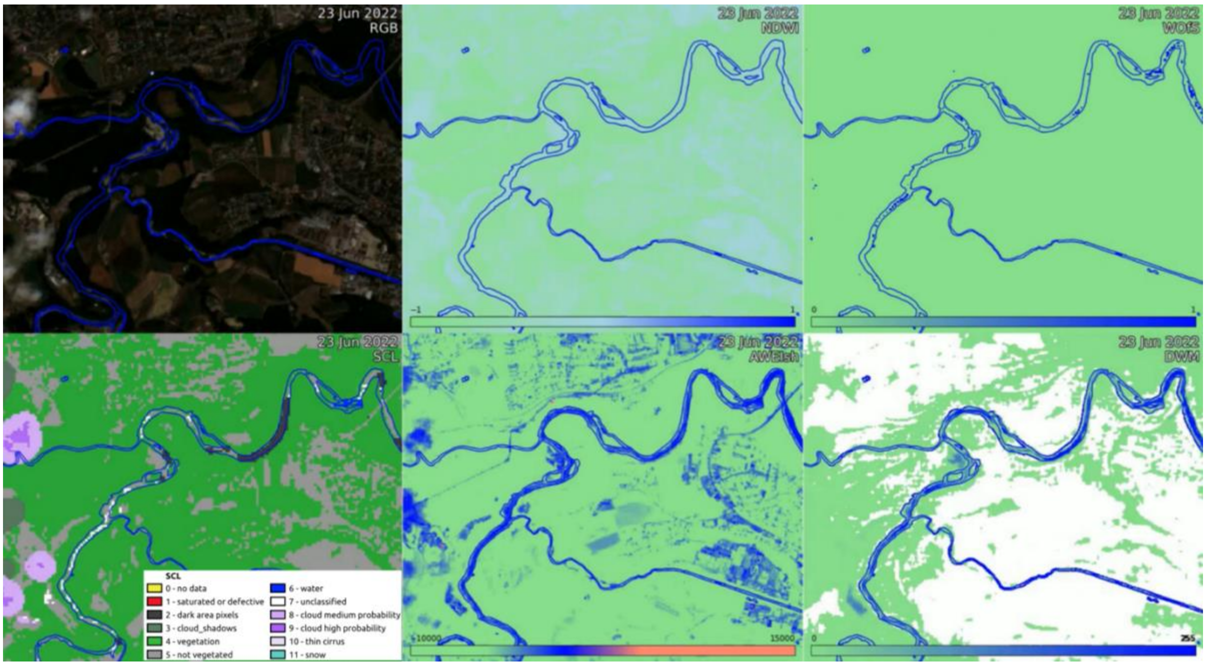
- ***AOI*** (Area of Interest): intersection of the very high-resolution imagery provided by project partner (Rapid Mapping (RM) and Geoeye 1 (GE1) of 13 August 2022) corresponding to 6.42, 7.19, 46.53, 46.87 (min_lon, max_lon, min_lat, max_lat) decimal degrees.
- ***Time period***: 1st of December 2016 to 28th of February 2023
- ***Indices***:
    - *NDWI*: Normalized difference Index ((G -N) / (G + N))
    - *AWEIsh*: Automated Water Extraction Index with Shadows Elimination (B + 2.5 * G - 1.5 * (N + S1) - 0.25 * S2)
    - WOfS: Water Observation from Space (complex algorithms using B, G, R, N, S1, S2)
    - *DWM*: DeepWaterMap (AI model using B, G, R, N, S1, S2)
- **Masking**:
    - Using SCL band and removing pixels categorized as “no data”, “saturated or defective”, “cloud medium probability” or “cloud high probability”
    - Riverbeds (see dedicated chapter below)
- **Aggregation**: mean of each indice and the number of scenes used in calculation were processed seasonally and monthly.
- **Seasons**:
    - DJF:December, January, February
    - MAM: March, April, May
    - JJA: June, July, August
    - SON: September, October, November

The figure below presents the applied workflow.



Riverbed

Used indices consist of mathematical combination of satellite imagery bands acting as a proxy of in our case pixel humidity. Consequently, false positive is common where pixels with different land cover type have the same indice value as can be seen in the AWEIsh section in the figure below, which is a screenshot of a movie showing raw data and revived indices through all the available period in a small area Southwest of Fribourg city (*all_indices.mp4* available in zipped annex provided with this document).



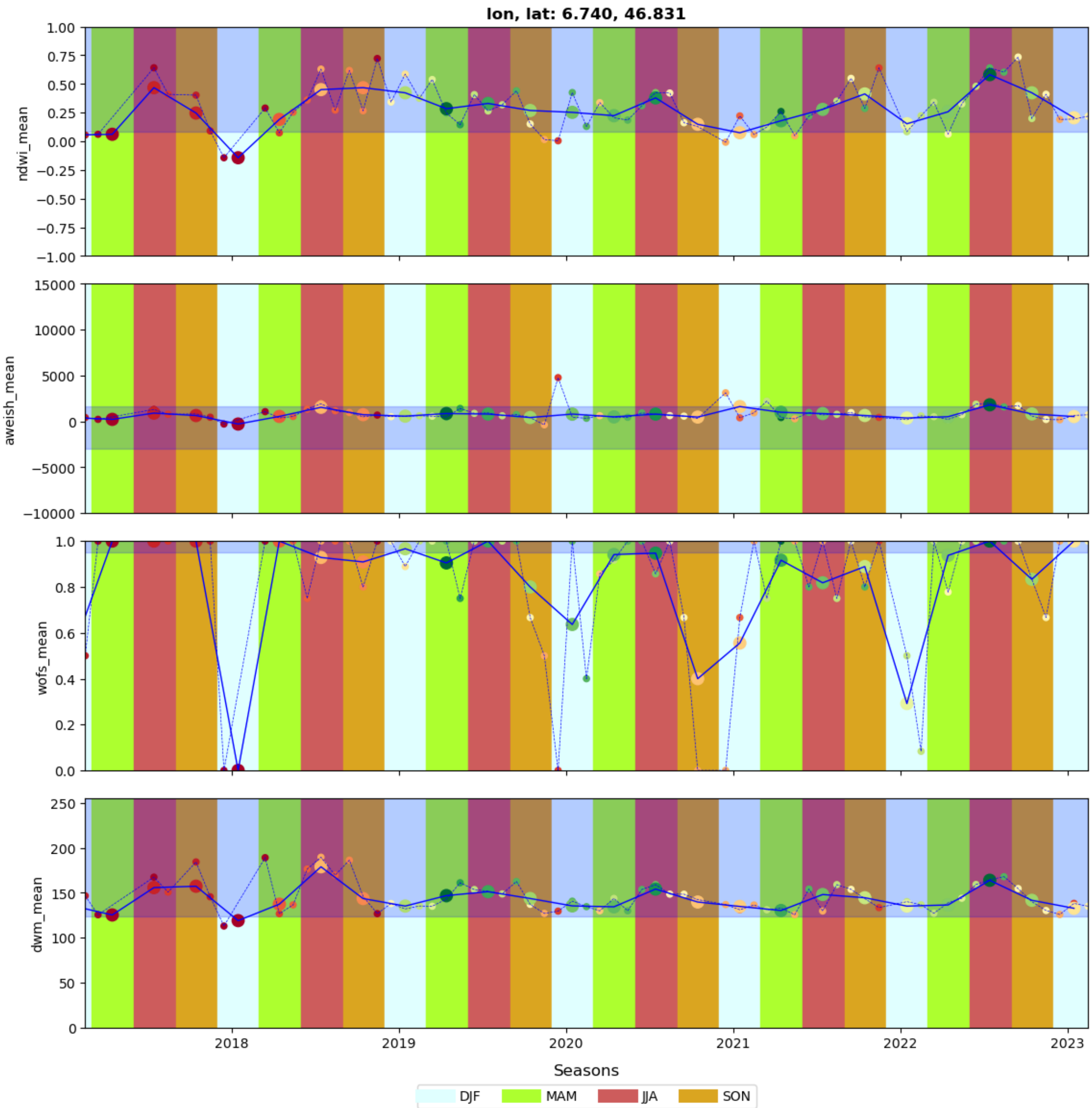
For this reason, we generated a “riverbed” layer and used it as mask to remove pixel located outside of the area to monitor.
This layer was created and used as follows:

1. Downloaded swissTLM3D (the large-scale topographic landscape model of Switzerland) from https://www.swisstopo.admin.ch/en/geodata/landscape/tlm3d.html.
2. Extraction of "Fliessgewaesser" (wintercourse) and "Stehende Gewaesser" (standing water) from "OBJEKTART" (object type) attribute.
3. Save layer as *swissTMN3D_riverbed_aoi.gpkg* (available in zipped annex provided with this document in the *s2_ts* subfolder).

During processing, the layer was loaded in the SDC instance, converted to an xarray.Dataset fitting the loaded Sentinel 2 xarray.Dataset (Coordinate Reference System and resolution). Then the riverbed mask was dilated by 1 pixel (10 meter) before being used as a mask.

Time series
The output of the workflow is available in a zipped annex provided with this document in the *s2_ts/ts_data* subfolder. It contains 2 type of water indices data:
s2_m_<yyyymm>.tif: Sentinel-2 indices monthly mean (yyyy: year, mm: month).
s2_s_<yyyymm>.tif: Sentinel-2 indices seasonal mean (mm corresponding to the middle season month).
Each geotiff also includes an *any_count* band corresponding to the number of values used for the mean calculation.
The *s2_ts* subfolder also contains a Jupyter notebook *s2_ts_plotter.ipynb,* which allows a user to plot water indices times series for a given location. User can refer to *README.md* or *README.pdf* for details on dependencies and installation.
Once a location is defined in the dynamic map, the script will generate figures such as:


Fontanezier
Villars-Burquin
Corcelles
Bonvillars
Onnens
Champagne
Fiez
Estavayer-le-Lac
Châtillon
Lully
Châbles
Cheyres
Bollion
Granges-de-Vesin
Aumont
Yvonand
Murist
Rovray
Cheseaux-Noréaz
Nuvilly
ipyleaflet | © OpenStreetMap contributors

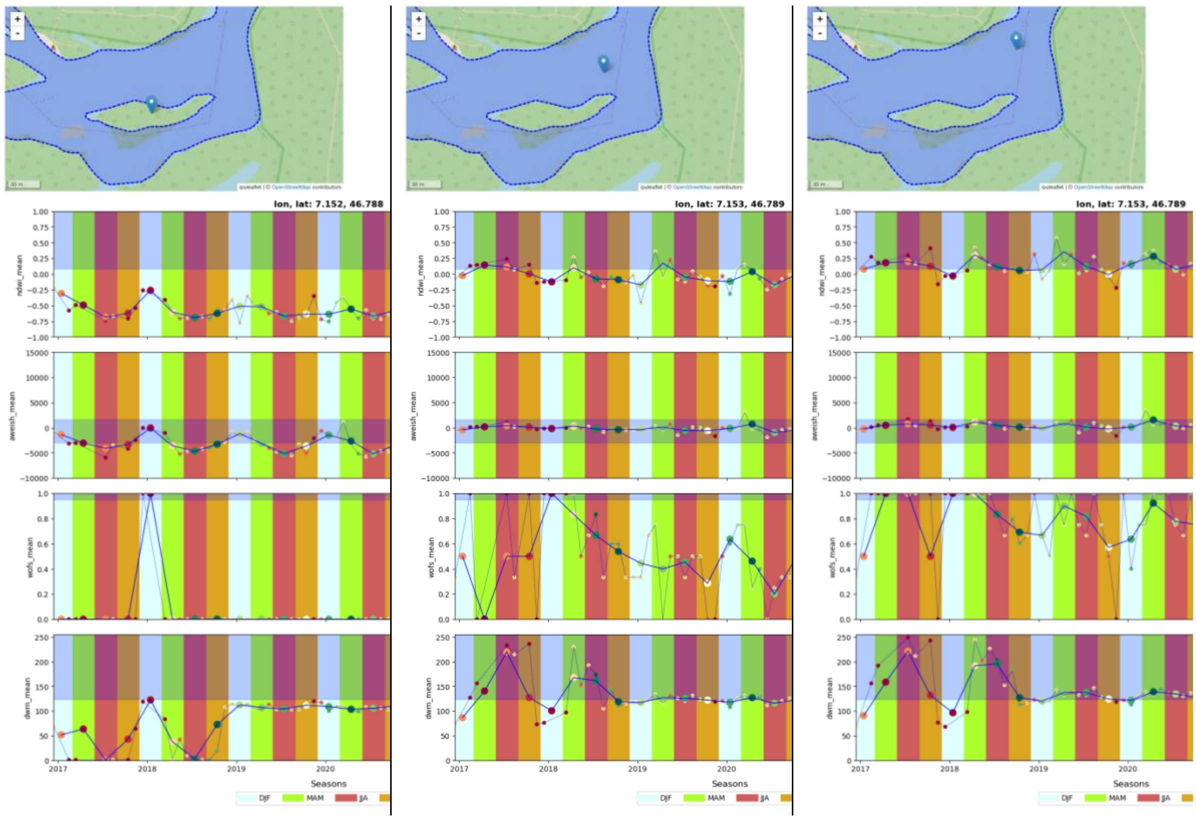

lon, lat: 6.740, 46.831
ndwi_mean
aweish_mean
wofs_mean
dwm_mean
2018
2019
2020
2021
2022
2023
Seasons
DJF
MAM
JJA
SON

- continuous blue line: seasonal values
- ticked blue line: monthly values
- big dots: colour representing a proxy of seasonal values quality (red: low, green: high)
- small dots: colour representing a proxy of monthly values quality (red: low, green: high)
- horizontal transparent blue rectangle corresponds to the range of values corresponding to water
- alternating light blue, green, red and orange correspond to seasons (see legend)

As can be seen in the Figure above, where the selected location is in the center of Lake of Neuchatel, and it should be detected as fully water.

- AWEIsh values are as expected with some values exceeding the expected water range, but only for very low quality
- NDWI and DWM values are in the lowest half of the expected range
- WOfS is clearly not realistic.

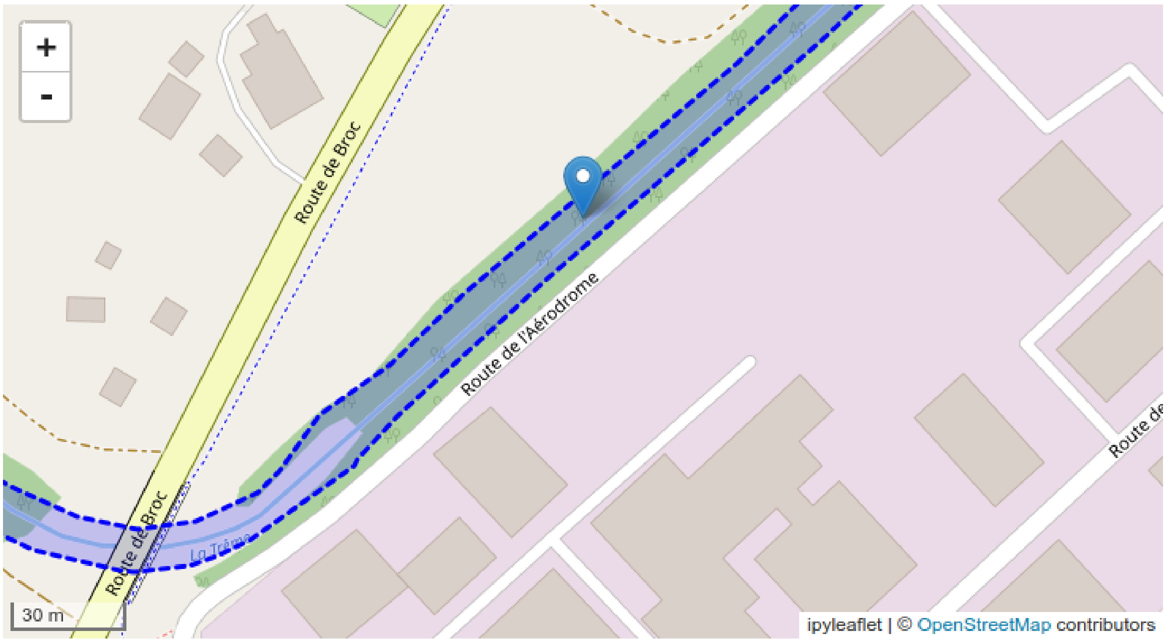
The next Figure presents a transect from a low elevation island, to “deep” water /left to right).

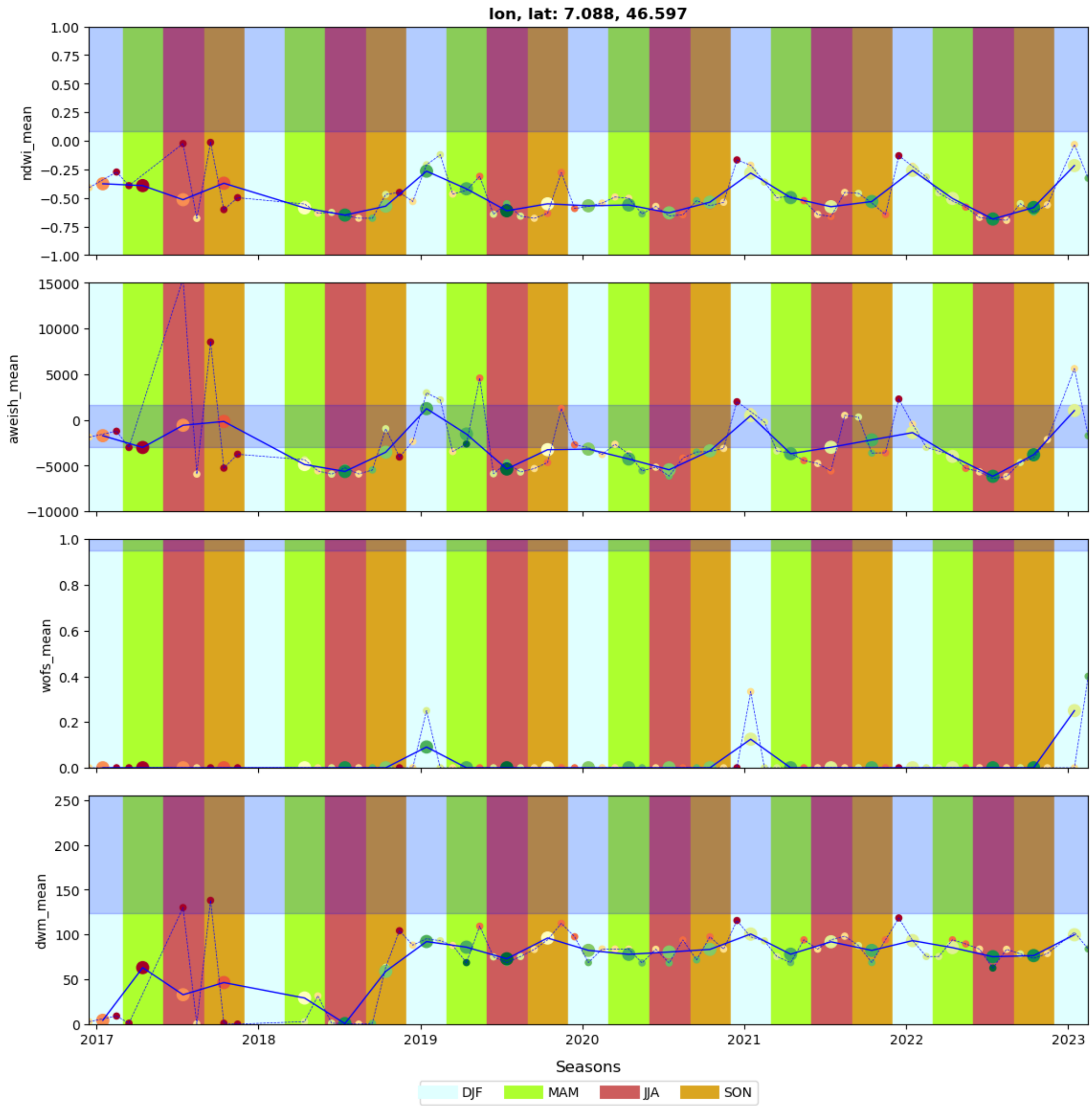


- AWEIsh and NDWI values are as expected (decreasing with water depth)
- WOfS values are clearly not realistic, but on the other hand this is the only indice showing a decreasing trend since 2018 (is the trend realistic?)

- The DWM values hover near the lower boundary of the minimum water range, but because it has been arbitrarily set as the midpoint of the DWM range, interpretation of such little variation remains uncertain.

Small river channels are not properly detected, except punctually by AWEIsh (next Figure).





3.4 Activity 4

Evaluation of the results (for example in a "water body vulnerability map") and identification of the difficulties or the need for further research.

Expected results: Report on the evaluation of results; identification of challenges; definition of improvements.

Impossible to do perform without data to be compared with and more precise definition:

- What needs to be measured (absence/presence of water, humidity, what is the humidity threshold?)

- Where (pixel based, section or river, what is a referential network of river, …)?
- When (on which temporal base (monthly, seasonally, yearly)?

Parts of these points are discussed in the Activity 5.

3.5 Activity 5

General assessment of the potential of aerial, drone, and satellite imagery for use during future drought events in Switzerland. Based on this, elaboration of a recommendation on how, where and when such remote sensing methods could be deployed in this context (incl. "cookbook recipe"/guidance for the use during drought periods).

Expected results: Final report with a general assessment of the tested methodology and literature review from Activity 1; set of recommendations; and cookbook to apply the methodology.

2. Orthophotos

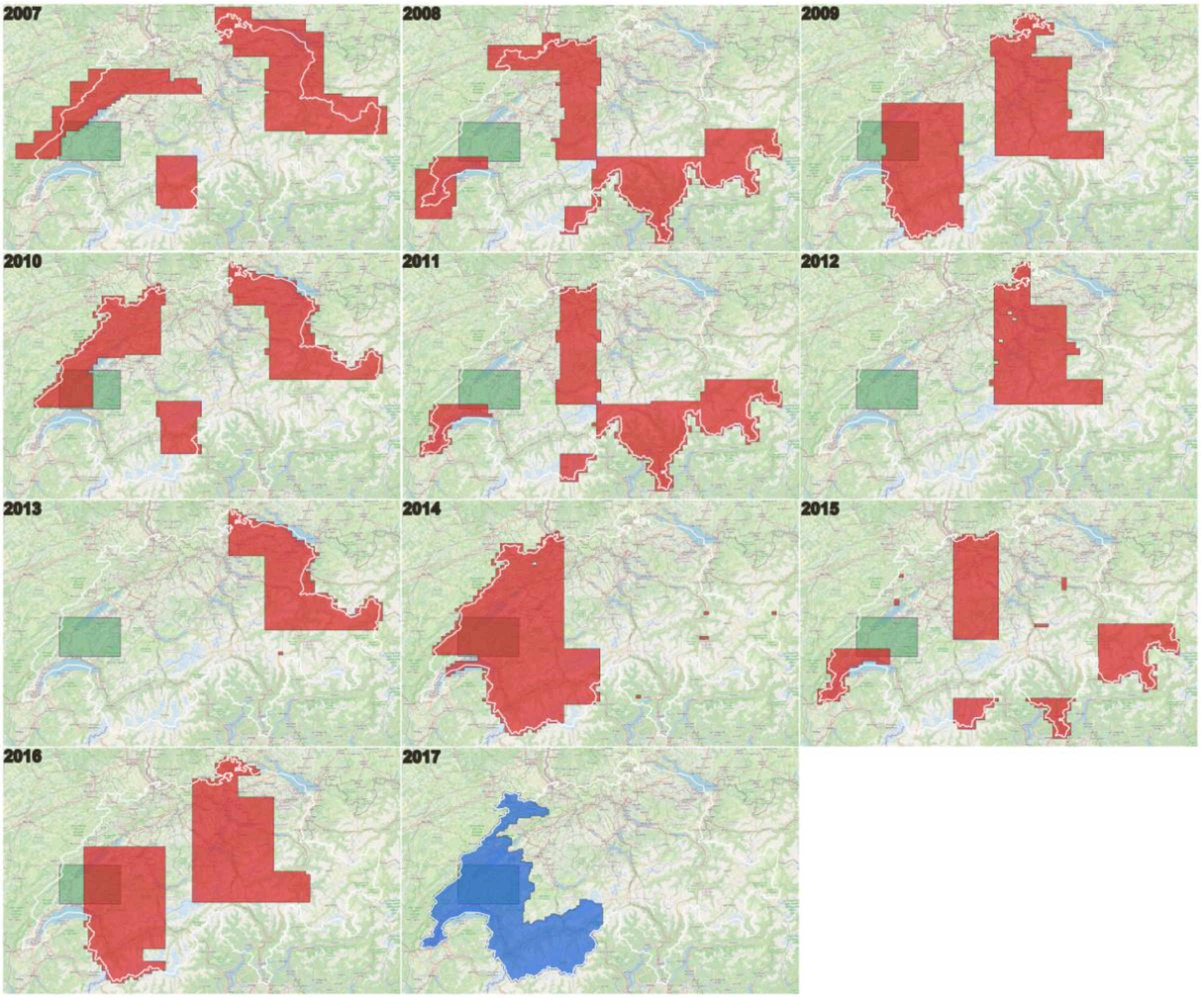
Two set of “yearly” (a dataset is released every year but does not cover all Switzerland) orthophotos are available 1) SWISSIMAGE 10 cm (“composition of new digital colour aerial photographs over the whole of Switzerland with a ground resolution of 10 cm in the plain areas and main alpine valleys and 25 cm over the Alps. It is updated in a cycle of 3 years”) composed of bands Red, Green, and Blue. And 2) SWISSIMAGE RS whichhave similar resolution but includes the band NIR (Near Infra-Red in addition to Red, Green, and Blue. Historically UNIGE has been keeping an archive of SWISSIMAGE 10 cm until 2017. Then two sources of data for SWISSIMAGE are available with surprisingly different content (as orthophotos available in UNIGE are not available in swisstopo anymore at the exception of year 2017).

2.1 SWISSIMAGE 10 at UNIGE

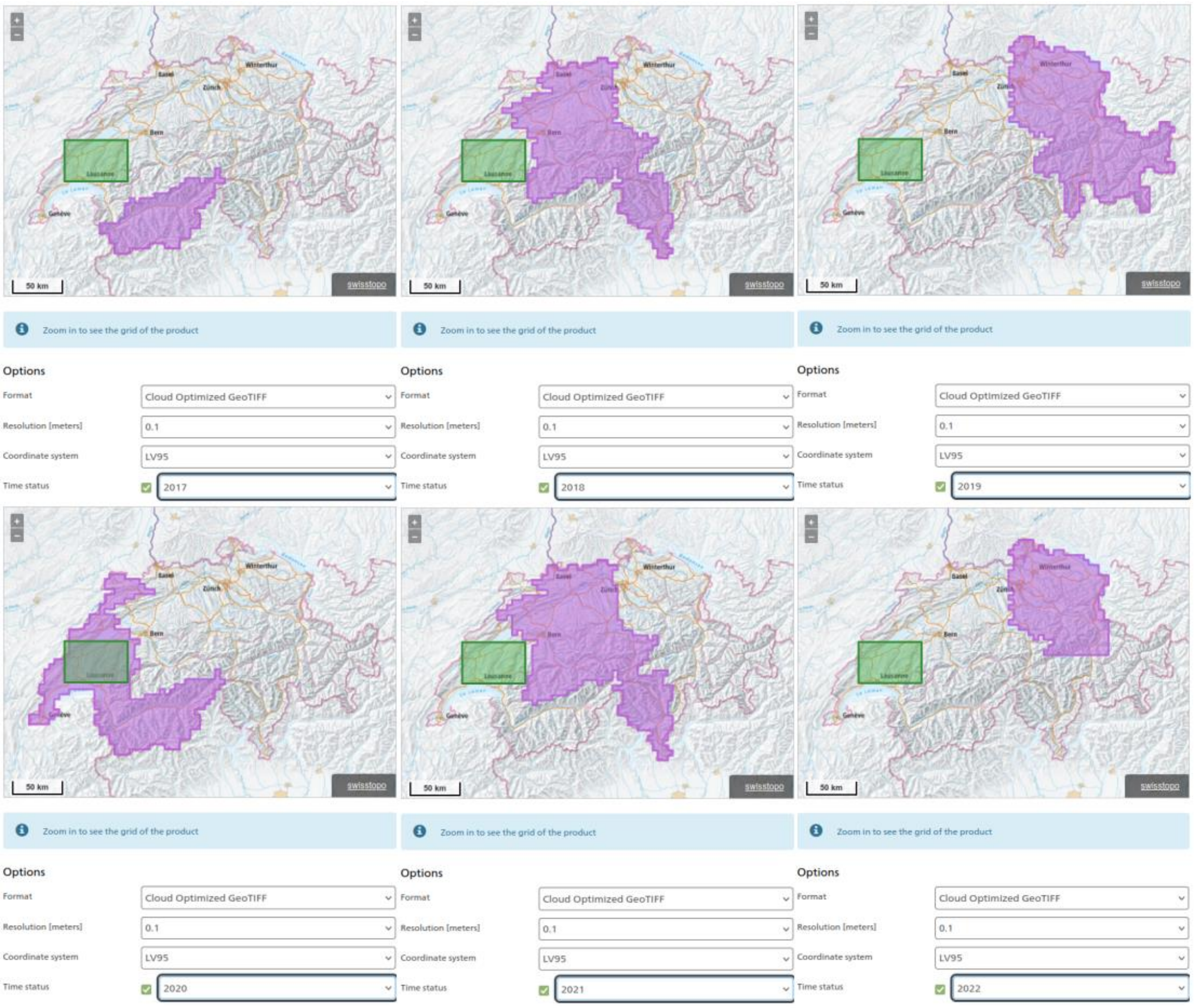
SWISSIMAGE 10 cm are available in UNIGE server from 2007 to 2017 in two different Coordinate Reference System (see Figure below presenting the acquisition region available for each year, study area in green, LV03 in red and LV95 in blue):

- CH1903 / LV03 (epsg:21781) from 2007 to 2016
- CH1903+ / LV95 (epsg:2056) for 2017

No metadata are available and as the original files are not available in swisstopo anymore, essential information such as acquisition date are missing.



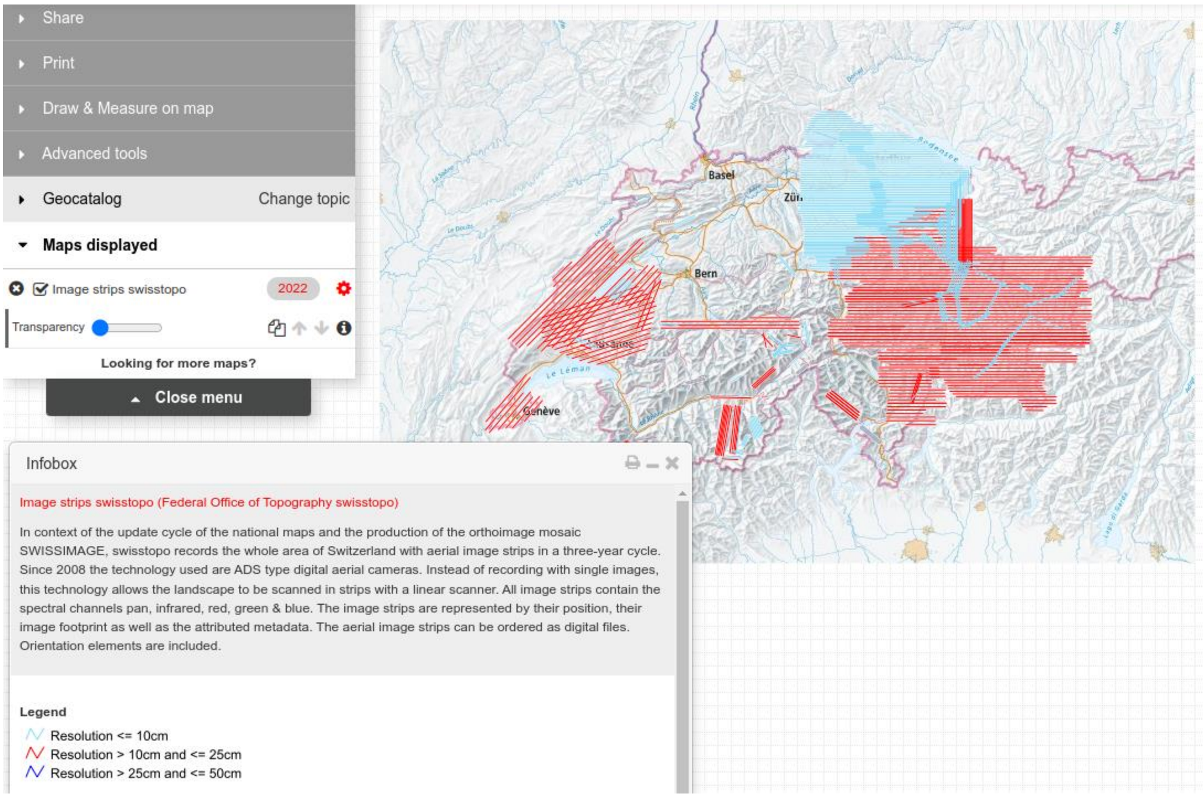
2.2 SWISSIMAGE 10 at swisstopo
SWISSIMAGE 10 cm are also available in swisstopo (see Figure below).



Images can be easily downloaded from https://www.swisstopo.admin.ch/en/geodata/images/ortho/swissimage10.html.
As in the case of UNIGE data, no metadata is provided when downloading the imagery, which explains the lack of metadata in UNIGE collection. Then acquisition date remains unknown!
Surprisingly the swisstopo website does not link datasets older than 2017, and more surprisingly coverage of dataset 2017 differs from the coverage of the same year available at UNIGE.
For the sake of demonstrating the SwissDataCube potential, imagery for 2020 were downloaded and added to the SwissDataCube.

2.3 SWISSIMAGE RS at swisstopo

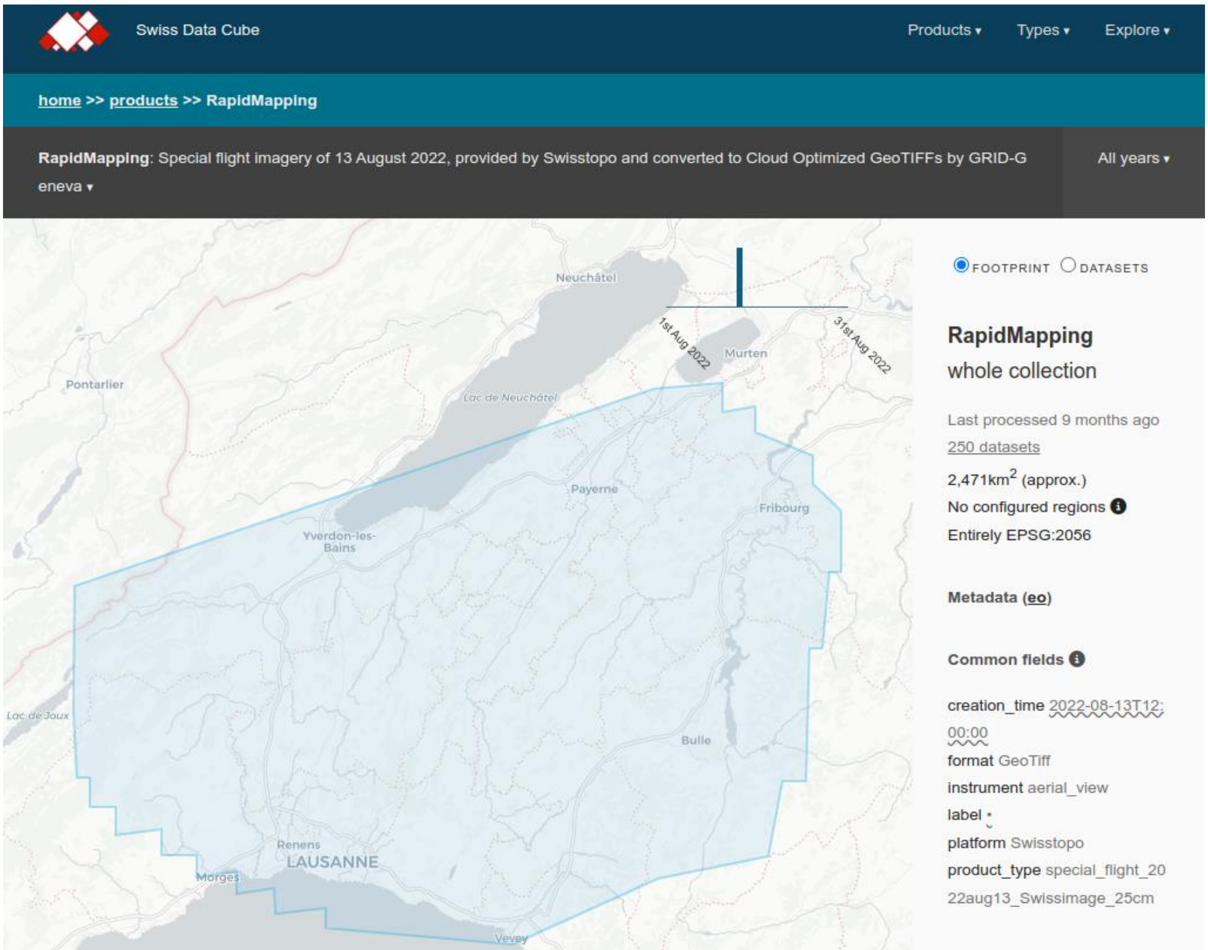
SWISSIMAGE RS are presented at https://www.swisstopo.admin.ch/en/geodata/images/ortho/swissimage-rs.html . Images with “completed” status are available from 2008 to 2022, but as the 10 cm product yearly dataset covers partially all Switzerland (see Figure below).



Unfortunately, the download cannot be performed from swisstopo website and the data needs to be ordered, processing time needs to be retributed, and data has to be shared via a hard disk provided by the person requesting the data and sent by post. Moreover, the volume of data to get needs to be kept "small".

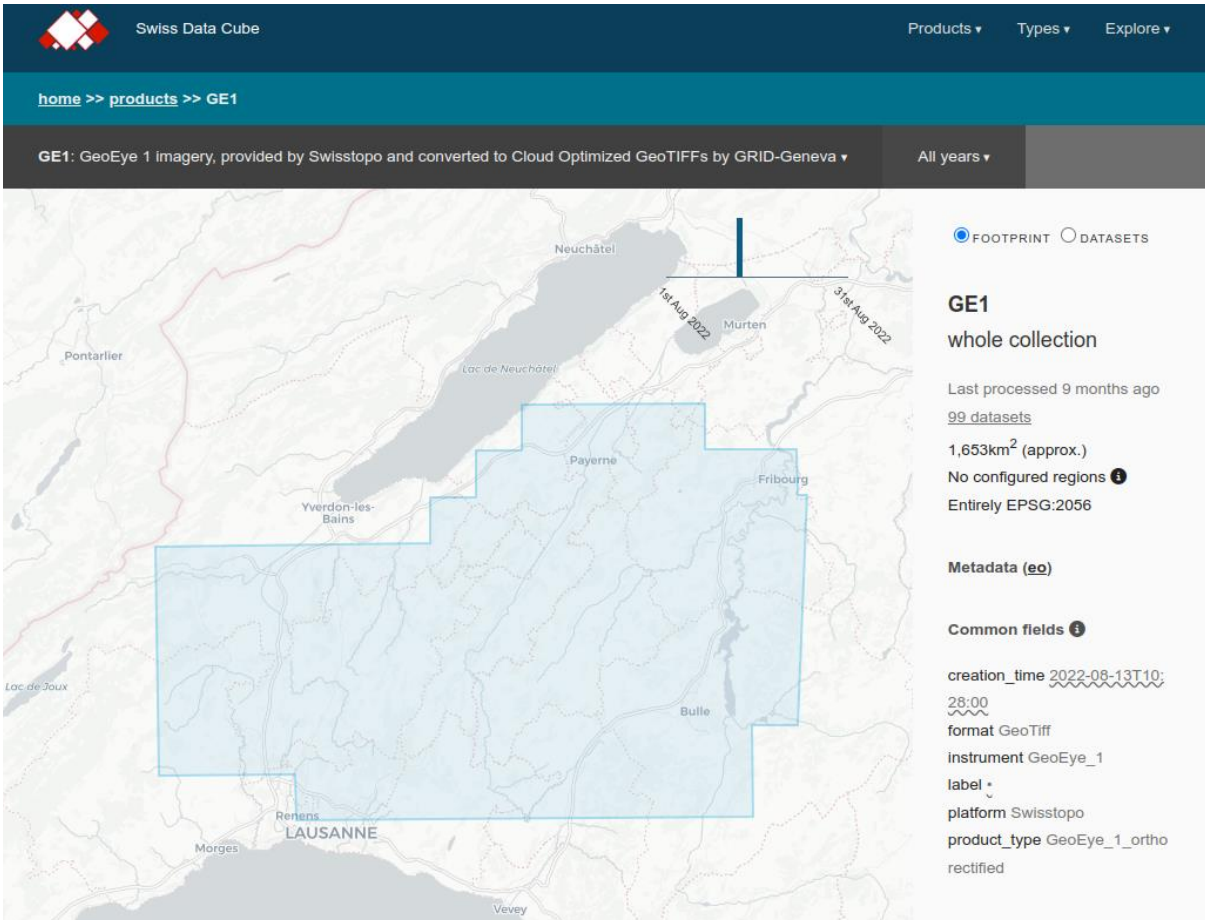
2.4 RapidMapping dataset

Orthophoto from a special flight operated the 13th of August 2022 by swisstopo was provided by the FOEN partner. The imagery contains the bands Red, Green, Blue and NIR at 25 cm resolution and was added to the SwissDataCube (https://www.swissdatacube.org). Metadata can be explored via the SwissDataCube Explorer (https://explorer.swissdatacube.org/products/RapidMapping), but due to restricted access policy, it cannot be downloaded.

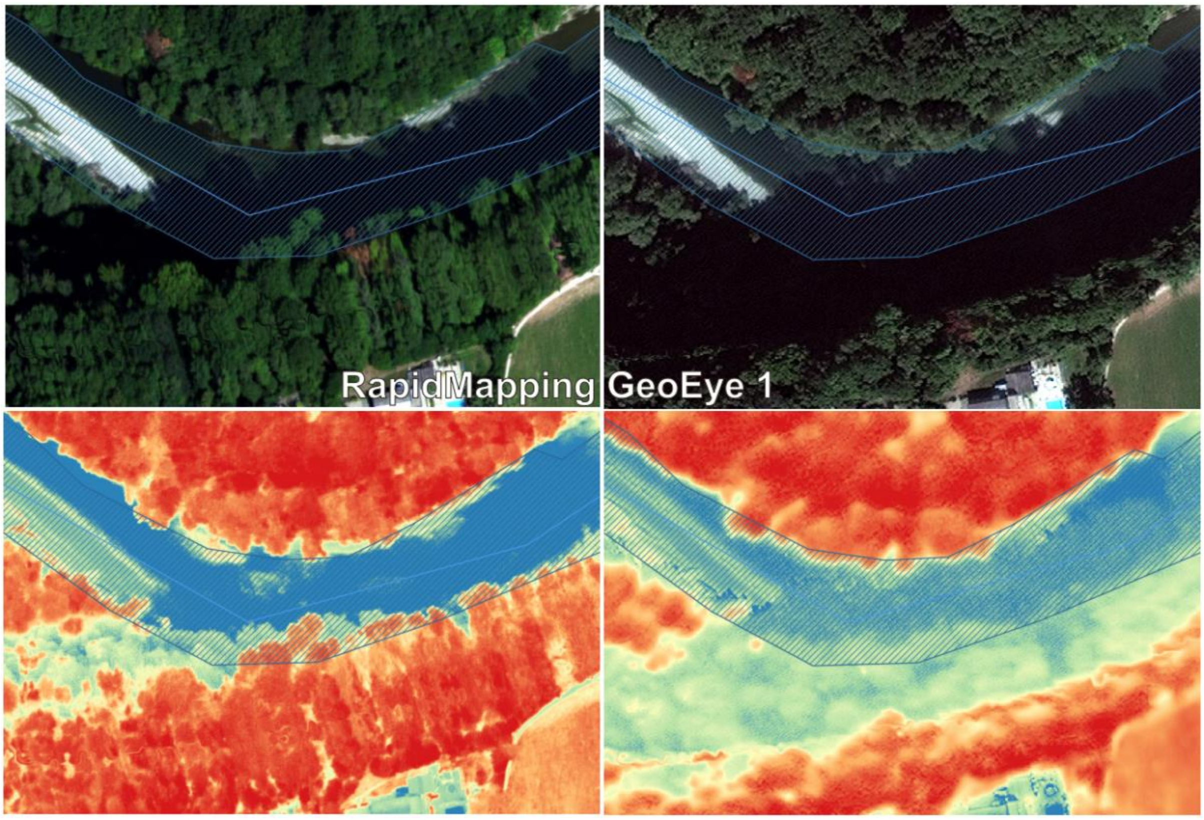


2.5 Geoeye 1 dataset

A GeoEye1 satellite dataset was also provided by FOEN for the same date as the RapidMapping dataset, containing the same bands (Red, Green, Blue, NIR) but at 40 cm resolution. It was also added to the SwissDataCube with the same restricted access.



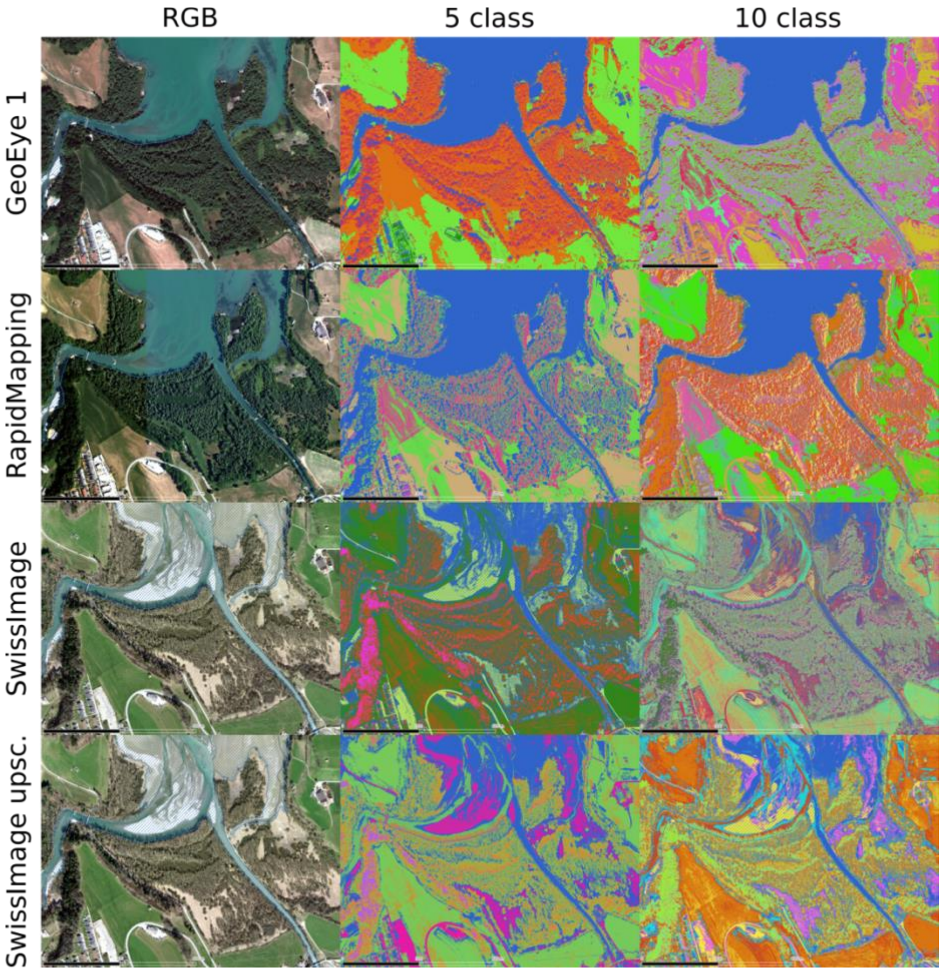
The limited number of bands of orthophotos and GeoEye 1 imagery allows only to compute NDWI. The Figure below shows how the indice is impacted by topography and vegetation shadow (riverbed in blue).

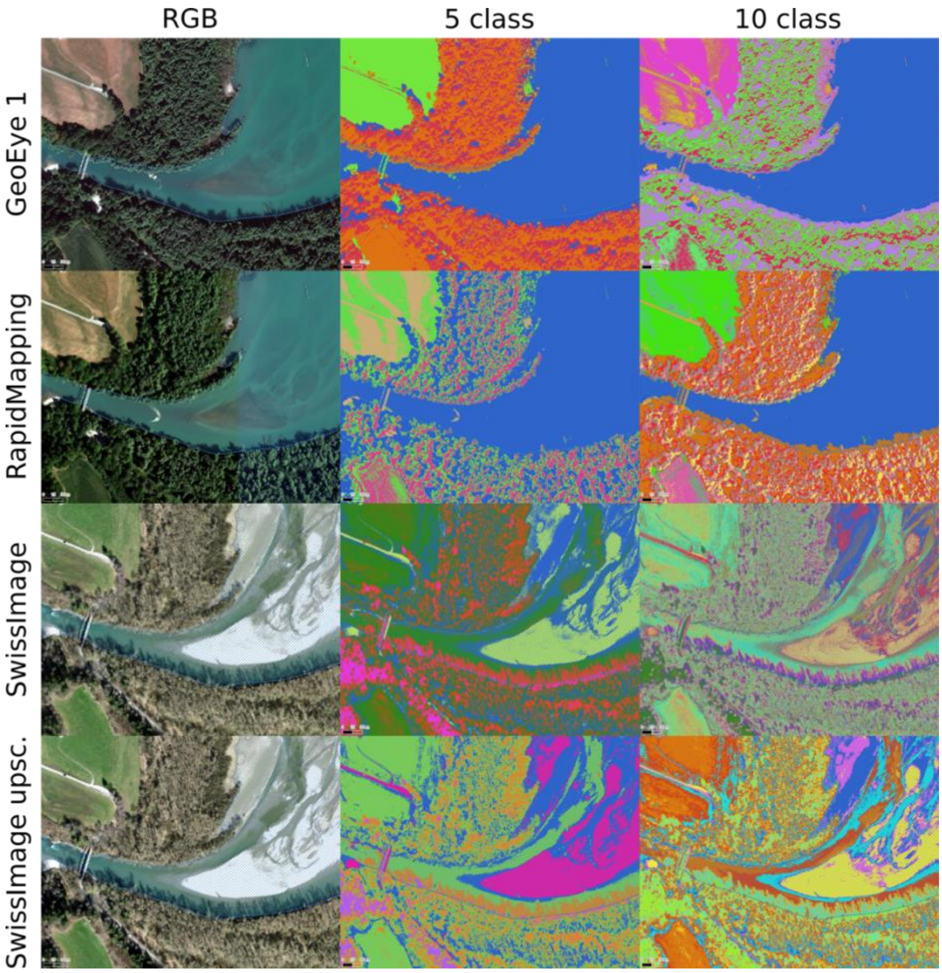

RapidMapping
GeoEye 1

2.6 Orthophotos useability for water monitoring

Unsupervised classification

Due to the lack of reference data unsupervised classification has been performed on a small test area of the HR imagery available. The two figures below present the result obtained when targeting 5 and 10 classes at two different scales. The water class is displayed in blue in all sub-figures.





SwissImage (10 cm) and RapidMapping (25cm) contain too much information to classify properly the water as a single class, and the second figure highlight the complication induced by oblique view (with pixel hidden by vegetation or vegetation shadow). It also shows how the GeoEye (40 cm) classification with 10 classes surprisingly allows to detect water even in shadowy areas.
One attempt has been done to upscale SwissImage resolution to 40 cm (SwissImage upsc. In figures above, using mean value), but without improving the classification result (which is probably due to the lack of NiR band).

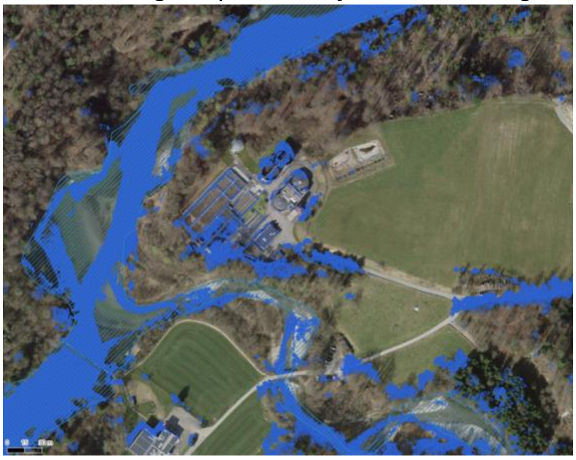
Following this exploratory phase, a 10 classes unsupervised classification has been performed on the full GeoEye dataset and converted into a "reference" dataset to be used in a second exporatory phase of supervised classification. The "reference" layer can be found in a zipped annex provided with this document in the *GE_classif* subfolder as GE_auto_water.gpkg and a description of how it was generated is available in Annex (GE "reference" dataset creation).

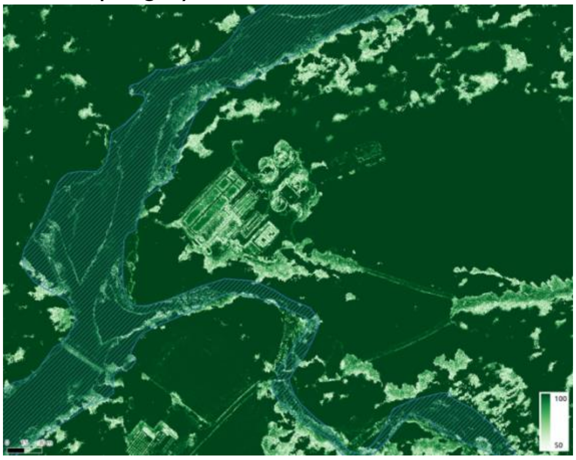
Supervised classification

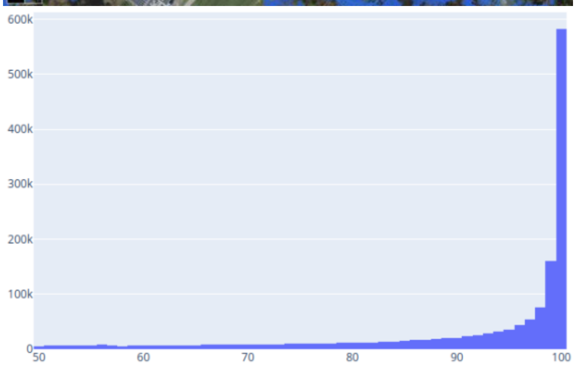
Once the "reference" dataset (*GE_auto_water.gpkg* available in zipped annex) uploaded into the SDC, another Jupyter script was run (*1_GE_sup_classif_extract_training.ipynb*) randomly sampling 10% of the pixels detected as pixels and the same amount of pixel classified as non-water and exported as .csv files (available as chunks in zipped annex *GE_classifGE_training* subfolder). Each .csv containing the following columns: x, y, blue, green, red, class (1: water, 0: non-water) totalling 11'514'672 pixels in total.

Then several supervised classification attempts were done using RandomForestClassifier from scikit-learn (https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html, due to the huge size of the dataset to process a full AOI classification was impossible in the allocated time. But the results are interesting to comment:

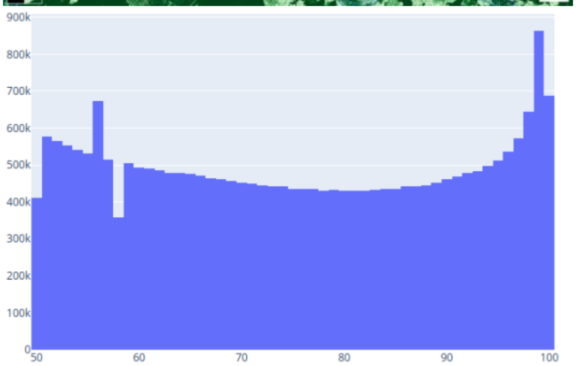
Water is predicted outside or riverbed (as any other method), but with a lower probability (the darker the higher probability in the next figure on the top-right) than outside of riverbed.





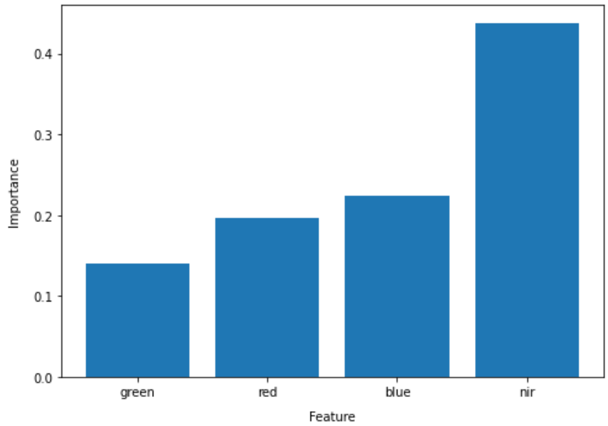


Distribution ow water probability in riverbed...

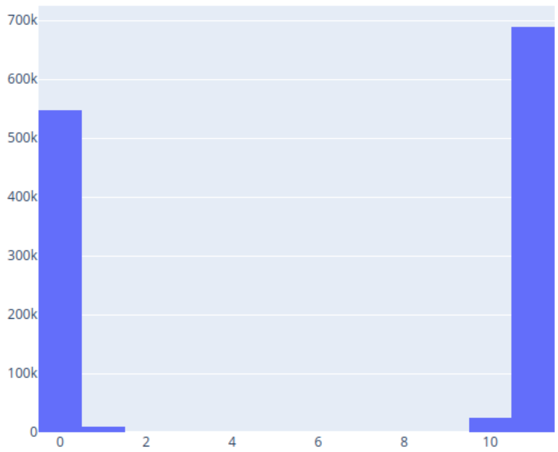


... and outside or riverbed

Preliminary result of training attempts confirmed how the NiR band is important as can be seen in the figure below representing the respective importance of each band.



Preliminary accuracy ranges between 0.95 and 0.98 which is pretty good with very minor difference between “reference” (unsupervised) and predicted as can be seen in the next figure (0: no water, 11: correctly predicted (light blue), 1: predicted only (deep blue), 10: reference only (red)).

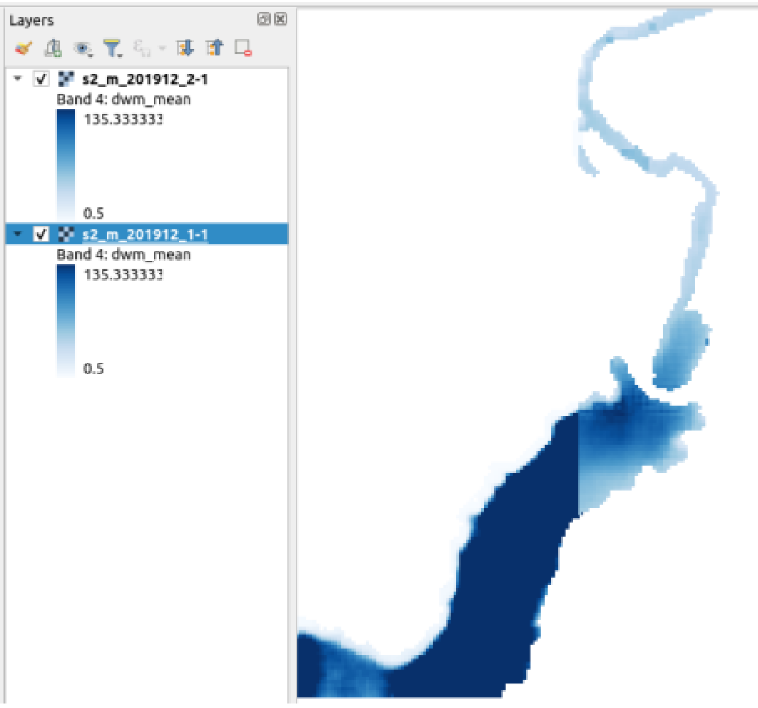


But such result is not surprising as the “reference” dataset and the prediction are using the same dataset and same type of classification algorithm.
Using a totally different reference (without “”) would probably decrease prediction accuracy.

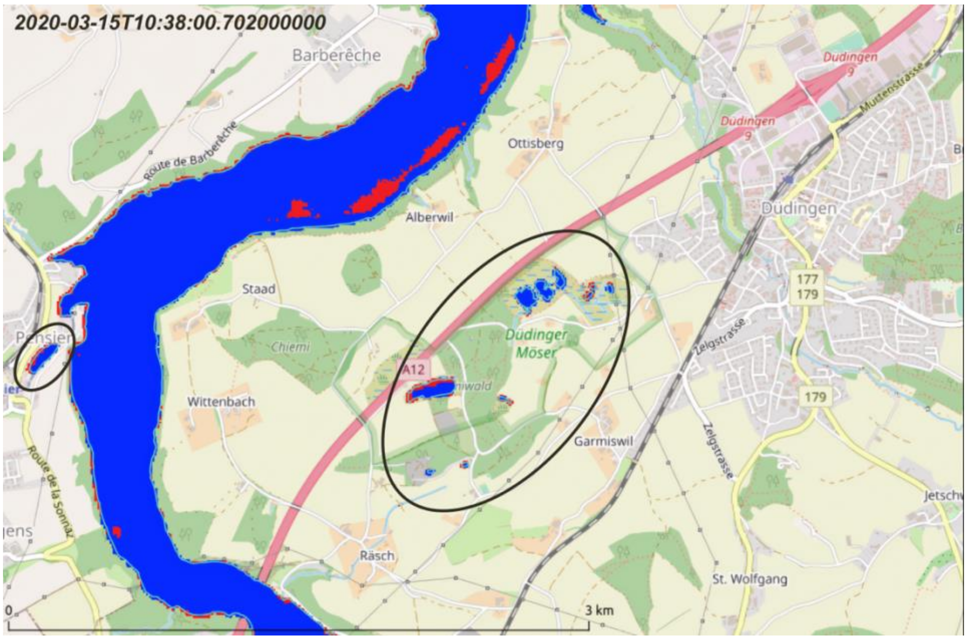
3. Lessons learned

- Sentinel 2 SCL water category barely represented.
- No single indice detects water fully.
- All indices detect humidity and not water body per se.

- NDWI and WOfS poorly represent water and fail totally in shadowy (surrounding topography and/or) areas.
- Sentinel 2 AWEIsh values for water between ~ –3000 and 1600
- Unsupervised classification with GeoEye gives visually (no external data are available to calibrate) good result but requires a lot of manual work to identify and extract the water classes from the chunked output (required when dealing with dataset too big to fit in memory).
- Supervised classification would require proper and consequent (we experimented with more than 10 Mio pixels) reference data, as well as important processing resources, without guarantee to get a better result than unsupervised classification.
- As only a single GeoEye dataset was available the useability of a single trained model on several GeoEye scene was impossible to test. But for sure:
    - Training should be done on several season or to have specific seasonal models,
    - Large computing power would be required.
- DWM interpret an image as a whole, then values will not be continuous between chunks.



- Riverbed layer includes small and isolated water bodies which might imply some cleaning.



- Riverbed layer is not always accurate -> mask with the area to monitor is required.

- Per pixel analysis not realistic, analysis per section might be more representative

AI analysis

Several AI solutions were explored, but only one was easily implemented in the project.

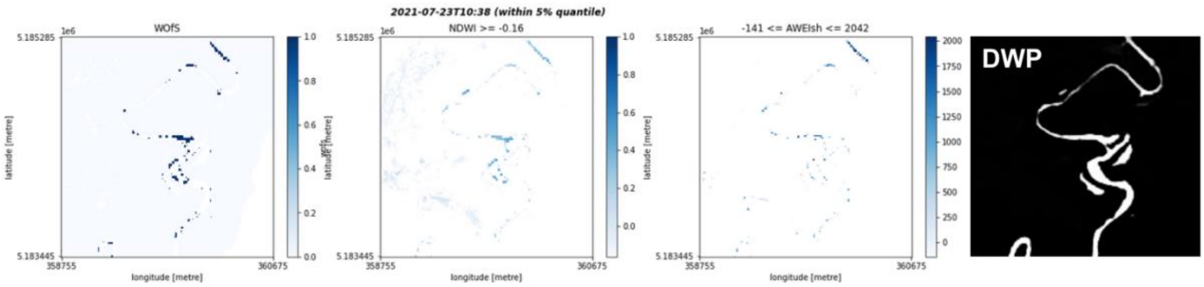
- AI needs to have a trained model, meaning training needs to be done on annotated data which are not available in Switzerland.
- Needs for an already trained model adapted to Switzerland context.

Deep Water Map

“DeepWaterMap is a deep convolutional neural network trained to segment surface water on multispectral imagery” (https://github.com/isikdogan/deepwatermap). Although the model was trained on Landsat-8 images only, it also supports data from a variety of other Earth observing satellites, including Landsat-5, Landsat-7, and Sentinel-2, without any further training or calibration.

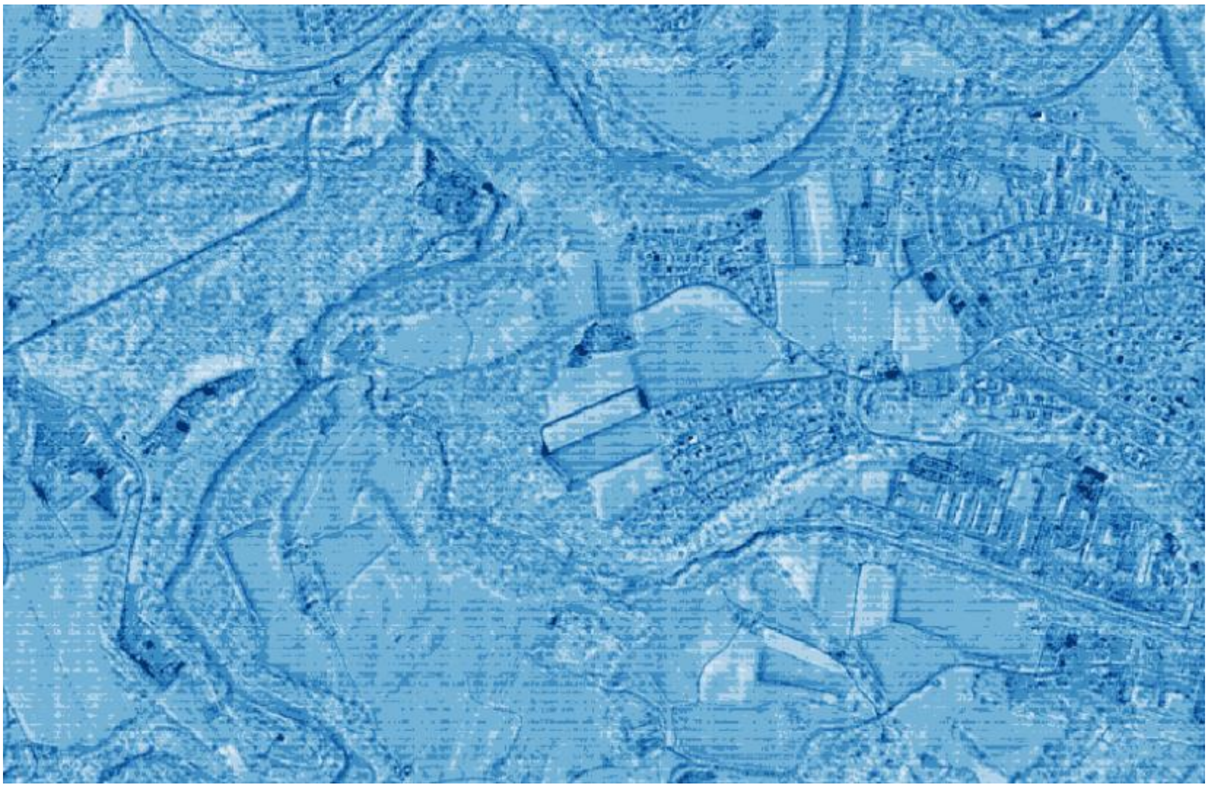
DWM as a 0.97 precision (proportion of correctly identified positive instances out of the total instances predicted as positive. It focuses on the accuracy of positive predictions), 0.90 recall (proportion of correctly identified positive instances out of the total actual positive instances. It focuses on the ability to find all positive instances) and 0.93 F1-score (single metric that combines both precision and recall into a harmonic mean. It provides a balanced measure of the model's overall performance).

Running DWM model on the project AOI provided results comparable and complementary to other traditional indices (see Figure below). But with an accuracy impossible to estimate due to the lack of annotated data.



Such results requires Red, Green, Blue, NIR, as well as SWIR (Short-Wave Infrared) 1 and 2. The two last bands are not available in orthophotos or GeoEye 1 imagery.

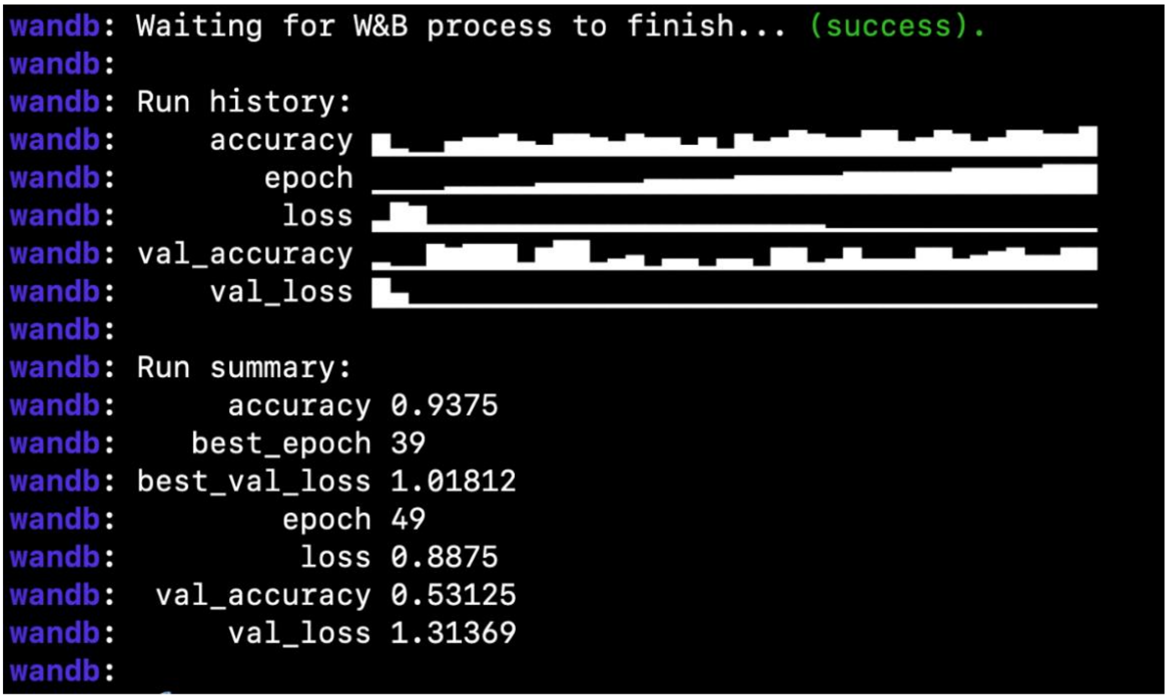
An attempt has been made to apply DWM model on a GeoEye 1 scene replacing SWIR bands values per 0 but gave poor results (see Figure below).



Exploring AI model for water monitoring

1. **Drought Watch** (https://wandb.ai/site/articles/droughtwatch) is a project aiming to improve drought detection using deep learning and satellite images. The project is part of the Weights & Biases Benchmarks (https://github.com/wandb/droughtwatch), which offers a centralised platform for open collaboration of deep learning projects. The prediction of drought conditions is done by learning a mapping from satellite images to forage quality, based on a dataset of 100'000 satellite images in North Kenya and manual labels of forage quality at corresponding geolocations.

We managed to clone the existing repository, install the required environment and train the existing model on our machines, using the given training set provided on the platform. The initial accuracy of the model was not as expected (around 36% accuracy) but we managed to tune the model and get an accuracy of 93% on the test data and 77% on the validation data.



Used existing data:
- 86’317 train images, stored in 400 TFRecords
- 10’777 validation images, stored in 100 TFReocrds
- Images are 65x65 pixels, 10 spectrum bands

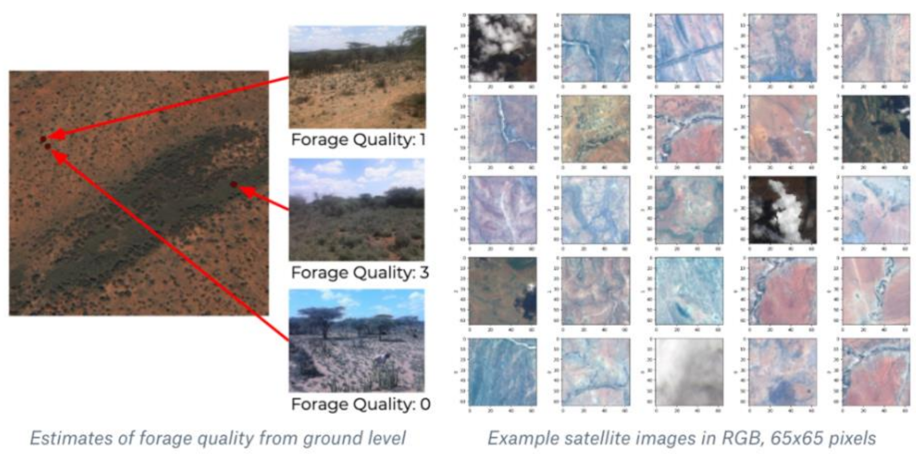
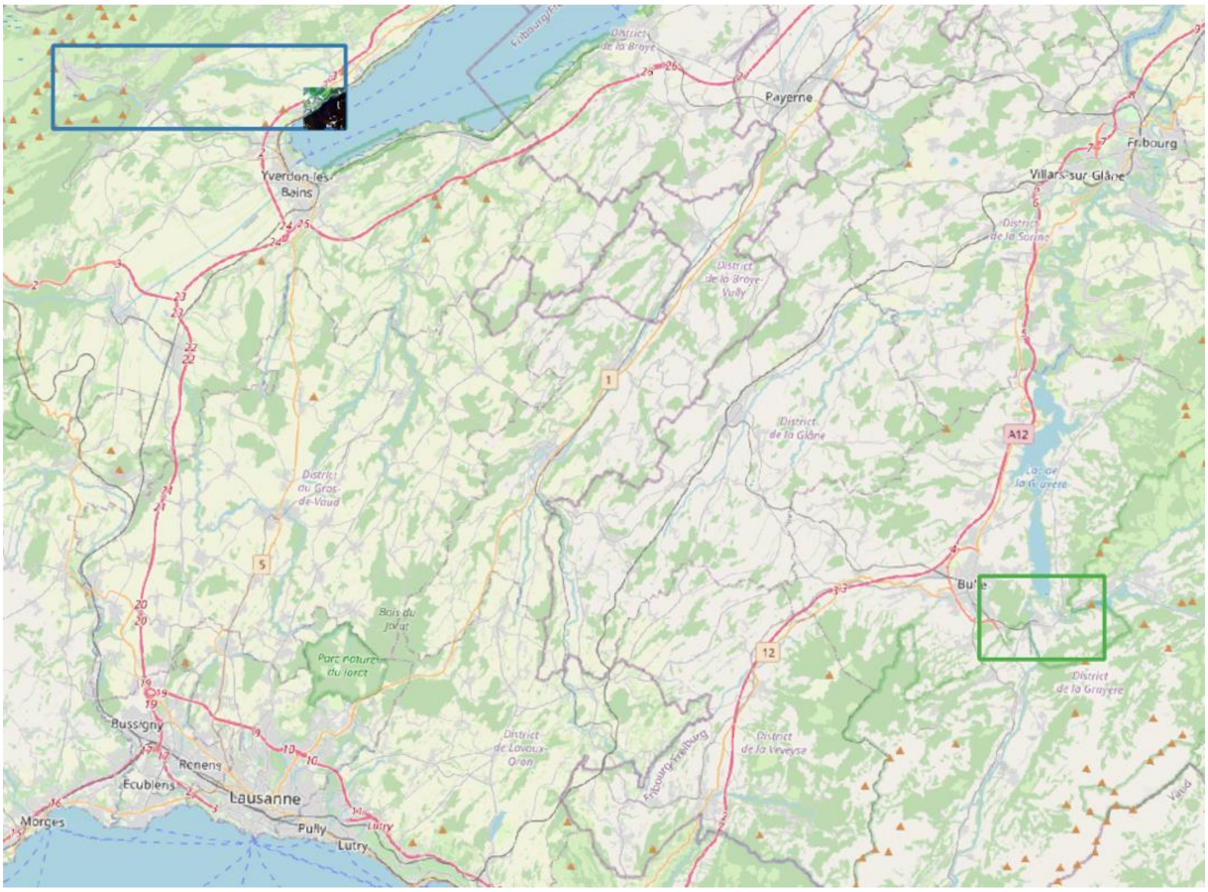


Figure 1: Images were labeled using pastoralist report of forage conditions on the ground.

-

Source: Satellite-based Prediction of Forage Conditions for Livestock in Northern Kenya, https://doi.org/10.48550/arXiv.2004.04081

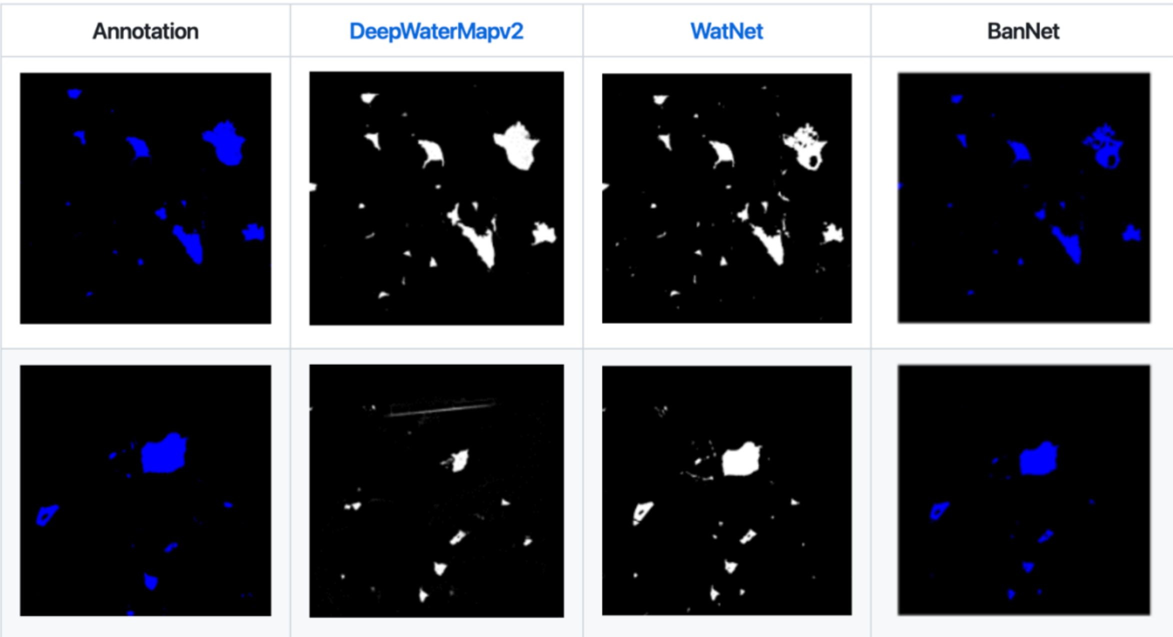
At Swiss level we wanted to explore the concept of Transfer learning and analyze if this is possible and efficient, based on the AI model trained in North Kenya. For this, we have selected two use cases in Switzerland, and we tried to get images with 65x65 tiles, for two areas 3 x 2 in green (urban) and 7x2 in blue (mountain to lake) - see figure below.



The tiles were exported in GeoTIFF but the conversion to the format required by the model (a particular format of TFRecords) was unfortunately not achieved yet as there is no information on data formatting on the Drought watch platform.
As many other existing open-source AI models, Drought Watch platform was a promising project but with no continuous support for the users or complete documentation on how to apply the model on other regions.

2. Another open-source AI model that was analyzed for water monitoring is the **BandNet**, described in Gupta et all, 2022 and available at: https://github.com/IamShubhamGupto/BandNet

The authors of BandNet affirm that overutilization or underutilization of the Sentinel-2 multispectral bands can lead to inferior performances in an AI model. The scope of their study was to compare the performance of several machine learning algorithms while using different cmbinations of bands for water segmentation. The conclusion of their work was that using only B11 reflectance data to train a neural network achieves a performance of more than 92% on the test site and it's much faster and better than other existing models, including DeepWaterMap.



Results of BandNet compared to DeepWaterMapv2 (https://github.com/isikdogan/deepwatermap) and WatNet (https://github.com/xinluo2018/WatNet)

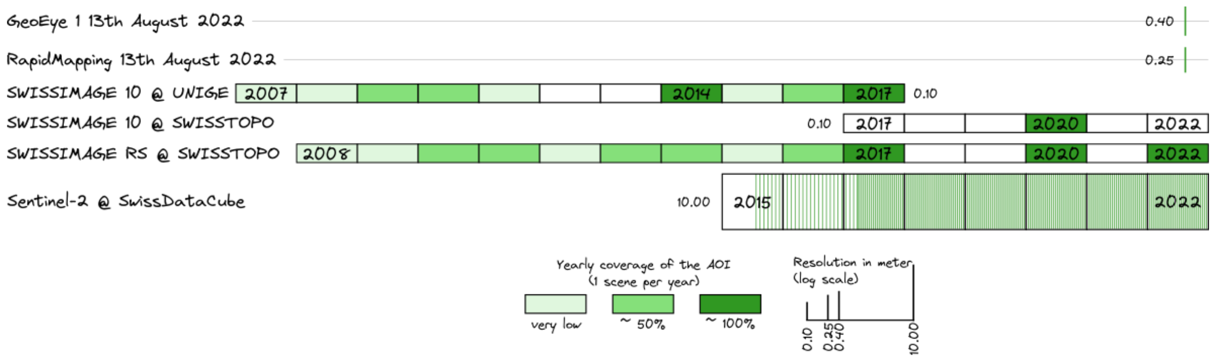
We contacted the authors to get the full training dataset or a trained model version to be applied on Sentinel 2 data over use cases in Switzerland, but this was not fully achieved. The model has a good potential, but as the authors admitted, it was only tested on a small region of interest and there is no evidence yet on how well the model will generalize on different areas, with different vegetation conditions.
To be able to test this model in Switzerland and asses it's performance, we need to create our own training and validation data sets (annotated Sentinel 2 images), which require more time and resources.

Reference:
Gupta, Shubham and D., Uma and Hebbar, Ramachandra, 2022, Analysis and application of multispectral data for water segmentation using machine learning, Computer Vision and Pattern Recognition, https://doi.org/10.48550/arXiv.2212.08749

4. Conclusions & Recommendations

Based on the different methods/sensors tested in the frame of this project and to develop efficient and effective monitoring methods based on EO data, it is essential to take into consideration the resolution in the spatial (size of the river vs. pixel res.), temporal (timing of the event vs. frequency of acquisition) and spectral scales (ability to extract information).
The ideal system would be a (V)HR & multi-spectral system that takes images on a weekly basis. Considering the different resolutions mentioned above, currently, it seems that VHR systems like WorldView/GeoEye, can be a promising solution. Indeed, it can provide regular, multi-spectral, high spatial resolution images. However, an important aspect to consider is the associated cost for regular acquisitions of such images.
Here are the main messages of the study:

1. There is a recent gain of interest on the topic with many recent publications demonstrating that EO data are useful and can provide valuable information.
2. Sentinel and Landsat data are interesting sensors but restricted to large rivers.
3. In the optical domain, Sentinel-2 outperforms Landsat 8 with better accuracy to extract river courses.
4. Aerial imageries are useful (but require at least RGB + NIR channels) but have never been used in a national operational system.
5. Time-series appear a promising (and a necessity) for efficient and effective change detection.
6. AI-related methods are emerging on this topic.
7. Superior accuracy and generalization ability of CNN, compared to rule-based and classical machine learning approaches.
8. Most of the existing AI models used to detect directly or indirectly the water bodies and water courses, are tested only on small uses cases, and when applied to other regions, they do not generalize well and do not achieve the same performance.
9. None of the identified services/applications can provide the necessary information for Switzerland.
10. We should develop our own national service using some of the identified methods.



Hereafter, we summarize the pros & cons of the different tested data sources/methods:

1. *High resolution with limited number of bands such as RGB orthophotos*
   - Makes nice visuals.

- Water extent is difficult to estimate precisely due to topographic, and vegetation shadow and oblique view.
- Cloud masking needs to be done manually.
- Are useless for water indices calculations.

2. *High resolution with a bit more bands (R, G, B, NIR) such as SWISSIMAGE RS or GeoEye 1*

- Have the same visual issues a RGB orthophotos.
- Cloud masking needs to be done manually.
- Allow to compute only NDWI.
- But study demonstrated that a single index is not sufficient to get a reliable and consistent identification of water.
- GeoEye 1 would allow continuous monitoring if acquired regularly.
- Images acquisition can be (extremely) costly (GeoEye 1, if acquired regularly; SWISSIMAGE RS)

3. *Medium resolution such as Sentinel 2 satellite imagery*

- Allow to compute multiple indices and perform AI analysis.
- Allow a continuous monitoring with approximately one image every week.
- But they lack precision and need to be aggregated in space (region instead of pixel) and time to be used to monitor water situation.
- All scenes are available for free on Swiss Data Cube, new scenes are automatically added when available, scenes are ready to be analysed with proper mask layer indicating cloud, cloud, shadow...
- Medium resolution does not allow to monitor small rivers.

4. *No single water index can accurately monitor water*

- A combination of indices is required.
- NDWI is the only index that can be calculated from orthophotos.

5. *AI need either*

- A trained model working on the study AOI (DWM seems to be a good candidate) but need annotated data to determine result accuracy.
- Big, annotated data to develop a model for the AOI study.
- No annotated data (small or big) are available.

6. *Radar imagery such as Sentinel 1 would a solution*

- Free to collect.
- Not affected by cloud, and shadows
- Needs an expertise different than analysing optical imagery.
- Could be added to Swiss Data Cube
- Medium resolution does not allow to monitor small rivers.

7. *SWISSIMAGE*

- Need proper metadata.
- The way SWISSIMAGE RS are distributed is complicated.

8. *Processing substantial number of medium resolution scenes or a limited number of very high-resolution scenes*

- Requires a consequent processing power (need HPC/cloud-based infrastructure).
- Requires processing AOI per tiles.
- AI interprets a dataset relatively (e.g., data with values between 0 and 10 will be interpreted the same way as 10 to 20, or 0 to 10). Meaning there will be discontinuities between tiles.

Finally, here are some recommendations for the next steps to fully benefit from EO data to contribute to monitor impacts of droughts on rivers:

- EO data can be helpful to monitor drying conditions of rivers, but this requires a good combination of different sensors for monitoring the diversity of rivers in Switzerland.
- Consequently, we think that a combination of optical and radar (Copernicus Sentinel-1 and 2) is the best option using freely available data for monitoring large rivers (e.g., Rhône, Rhine, etc...)
- GeoEye appears to be a relevant choice with its high spatial-resolution and multi-spectral capabilities (essential for effective extraction of water information) to monitor small rivers.
- It is fundamental to define a baseline period (i.e., normal conditions) to facilitate the comparison with drying events.
- It is also essential to have a proper riverbed layer (possibly cut into sections to monitor) to compare with extracted water information for EO data.
- Time (to capture rapid onset event) and spectral (true-color images are not sufficient) dimensions are a prerequisite.
- Machine/Deep Learning techniques appears very interesting to extract relevant information but requiring developing good quality reference/annotated data for training and validation.

ANNEXES
Activity 1

Literature review on techniques and current applications and their accuracy to detect dry watercourse sections during drought periods using (very-) high resolution aerial, drone, and satellite imagery.

Expected results: Identification of the candidate techniques to be tested, short summary of the literature review and current applications (to be included in Activity 5), as well as possible accuracy assessment and validation to be applied in Activity 3-4.

Objective of the project: Potential of remote sensing data and other methods to collect information during drought such as location of dry watercourse section.

Articles review

1. **Gao S. et al. (2021)** ***Monitoring Drought through the Lens of Landsat: Drying of Rivers during the California Droughts*** **https://doi.org/10.3390/rs13173423**

Sensor(s): Landsat; ***Method(s):*** Landsat-based Global Surface Water (GSW), monthly time series of fractional river extent, average surface water presence, in-situ data; ***Message(s):*** The Landsat provides consistent observations of over 90% of the river area within bankful widths from March to October, but poor observations from November to February, making it a viable source for monitoring rivers' seasonal drying dynamics (from spring to fall); The 30-m resolution causes potential underestimation of FrcSA during low flow conditions; detectability of Landsat on the river surface extent in an arid region with complex terrain.

2. **https://www.climatechangenews.com/2022/08/26/visuals-extreme-drought-dries-up-rivers-globe-satellite-images/**

Sensor(s): Landsat; ***Method(s):*** Before/After; ***Message(s):*** Satellite data suitable to visualize the change

3. **Vanderhoof & Lane (2021)** ***The potential role of very high-resolution imagery to characterise lake, wetland and stream systems across the Prairie Pothole Region, United States*** **https://doi.org/10.1080%2F01431161.2019.1582112**

Sensor(s): Landsat - pan-sharpened high-resolution (PSHR) imagery; ***Method(s):*** matched filtering algorithm (MF Landsat), GSW, ; ***Message(s):*** The PSHR outputs (and MF Landsat) were able to identify ~60–90% more surface water interactions between waterbodies, relative to the GSW Landsat product

4. **Wieland & Martinis (2020)** ***Large-scale surface water change observed by Sentinel-2 during the 2018 drought in Geny*** **ttps://doi.org/10.1080/01431161.2020.1723817**

Sensor(s): Sentinel-2 ; ***Method(s):*** mosaic(R,G,B,NIR,SWIR1,SWIR2), CNN & semantic segmentation, change detection & labelling; ***Message(s):*** Sentinel-2 data provided sufficiently high spatial and temporal resolutions to monitor surface water changes with high precision in short time, over large areas and free of (data) costs; mean effective revisit period = 7.5d; automated workflow; able to detect and quantify small-scale changes in surface water extent as well as change hotspots at national scale; insights into the spatio-temporal dynamics of surface water changes; process raw satellite data into actionable information products that can provide rapid situational awareness in drought situations; need to integrate in-situ data; Rule-based methods may be transparent and produce accurate results under specific conditions, but they largely lack generalization ability and transferability between sensors, geographies, and scene properties (NDWI, MNDWI, MBWI, AWEI, HRWI); superior accuracy and generalization ability of CNN, compared to rule-based and classical machine learning approaches.

5. Li et al. (2020) *Open-Surface River Extraction Based on Sentinel-2 MSI Imagery and DEM Data: Case Study of the Upper Yellow River* https://doi.org/10.3390/rs12172737
Sensor(s): Sentinel-2 ; ***Method(s):*** Data fusion (S2 & 90m DEM), MNDWI-RNDWI.AWEI + Otsu threshold method; ***Message(s):*** The effective river width that can be accurately extracted based on satellite images is three times the image resolution. Sentinel-2 MSI images with a spatial resolution of 10 m are used to find that the rivers over 30 m wide can be connectedly, accurately extracted with the proposed method; provide a foundation for studying the spatiotemporal changes in channel geometry of river systems.

6. https://www.esa.int/ESA_Multimedia/Images/2022/06/Po_River_dries_up
Sensor(s): Sentinel-2 ; ***Method(s):*** Before/After ; ***Message(s):*** Satellite data suitable to visualize the change

7. Tian et al. (2020) *High Spatiotemporal Resolution Mapping of Surface Water in the Southwest Poyang Lake and Its Responses to Climate Oscillations* https://doi.org/10.3390%2Fs20174872
Sensor(s): Sentinel-1 ; ***Method(s):*** Sentinel-1 water index (SWI) and SWI-based water extraction model (SWIM); ***Message(s):*** The automated water extraction algorithm proposed in this study has potential applications in delineating surface water dynamics at broad geographic scales

8. Sogno et al. (2022) *Remote Sensing of Surface Water Dynamics in the Context of Global Change—A Review* https://doi.org/10.3390/rs14102475
Sensor(s): Multiple; ***Method(s):*** Review; ***Message(s):*** Until the start of the Sentinel fleet, widely accessible data has always seen a duality of either high spatial or high temporal resolution; Due to their sensitivity to cloud cover and the confinement to daytime observations, optical sensors are not always an ideal choice for the analysis of surface water dynamics. Active and passive microwave sensors are valuable complementary assets as they can observe surface water through cloud and even vegetation cover (depending on the used wavelength); time-series enables inter and intra-annual dynamics; The choice of sensor is mostly determined by the focus of a study (i.e., intra- vs. inter-annual dynamics), its area of

interest, and the length of the considered timeframe; Due to the high spatial resolution, the long continuity, and the availability of multiple analysis-ready products, the vast majority of studies work with Landsat data; Surface water delineation > mostly done through unsupervised classification techniques + thresholding; In SAR data, water is discernable due to its low backscatter intensity; supervised classification with Machine Learning techniques is an emerging trend; Global dataset have several drawbacks that limit their accuracy and usability (e.g., cloud-covered regions, lack of temporal resolution with Landsat…); The increased availability of satellite constellations like the Sentinel fleet ensures increased data availability with high spatial and temporal resolution data; high potential in the use of multi-sensor approaches.

9. **Ogilivie et al. (2018)** ***Surface water monitoring in small water bodies: potential and limits of multi-sensor Landsat time series*** **https://doi.org/10.5194/hess-22-4349-2018**
Sensor(s): Landsat ; ***Method(s):*** Modified Normalised Difference Water Index (MNDWI) ; ***Message(s):*** mostly for lake/flooding dynamics
10. **Kulkarni et al. (2022)** ***Detecting, extracting, and mapping of inland surface water using Landsat 8 Operational Land Imager: A case study of Pune district, India*** **https://doi.org/10.12688/f1000research.121740.1**
Sensor(s): Landsat ; ***Method(s):*** MNDWI ; ***Message(s):*** MNDWI is easy to implement and is a sufficiently accurate method to separate water bodies from satellite images. The accuracy of the result depends on the clarity of image and selection of an optimum threshold method. The resulting accuracy and performance of the proposed algorithm will improve with implementation of automatic threshold selection methods

11. **Li et al. (2021)** ***Accurate extraction of surface water in complex environment based on Google Earth Engine and Sentinel-2*** **https://doi.org/10.1371%2Fjournal.pone.0253209**
Sensor(s): Sentinel-2 ; ***Method(s):*** automatic water extraction model in complex environment(AWECE); using wetness of Tasseled Cap + SVM for cloud detection + automatics thresholding ; Message(s): MNDWI has poor results in extracting small rivers; AWECE model provides an effective solution for the precise extraction of surface water in complex environments and has important practical significance for water resource investigation, monitoring, and protection.

12. **Vidal-Abarca (2020)** ***Defining Dry Rivers as the Most Extreme Type of Non-Perennial Fluvial Ecosystems*** **https://doi.org/10.3390/su12177202**
Sensor(s): N/A ; ***Method(s):*** N/A ; ***Message(s):*** Dry Rivers as non-perennial rivers with their own ecological identity with significant roles in the landscape, biodiversity and nutrient cycles, and society; thus worthy to be considered, especially in the face of exacerbated hydrological drying in many rivers across the world.

13. **Thiessen (2019)** ***Automating Surface Water Detection for Rivers: Estimation of the Geometry of Rivers based on Optical EO sensors***

https://www.utwente.nl/en/et/cem/research/wem/education/msc-thesis/2019/thissen.pdf
Sensor(s): Landsat, Sentinel-2; ***Method(s):*** Water indices, HAND-map, thresholding; ***Message(s):*** the estimation of the geometry of rivers in a more or less automated manner was found to be achievable, its global applicability remains limited to a local scale; the estimation of the geometry of a river is found to be limited to rivers
that are at least three to four times wider than the corresponding satellite's spatial resolution in order to obtain usable results.

14. Ijaz et al. (2017) ***Detection of Hydromorphologic Characteristics of Indus River Estuary, Pakistan, Using Satellite and Field Data*** https://doi.org/10.1007/s13369-017-2528-9
Sensor(s): Landsat ; ***Method(s):*** supervised classification ; ***Message(s):*** the shortwave infrared-2 (band 7) of Landsat-8 Operational Land Imager (OLI) sensor performed better than its visible bands for delineating water bodies; selecting the spatial resolution of the imagery should be based on the size of the objects to be recognized.

15. Bioresita et al. (2019) ***Fusion of Sentinel-1 and Sentinel-2 image time series for permanent and temporary surface water mapping*** https://doi.org/10.1080/01431161.2019.1624869
Sensor(s): Sentinel-1, Sentinel-2 ; ***Method(s):*** Data fusion ; ***Message(s):*** combination of Sentinel-1 & 2 observations provides better accuracy for mapping permanent surface water

16. Obida et al. (2019) ***River network delineation from Sentinel-1 SAR data*** https://doi.org/10.1016/j.jag.2019.101910
Sensor(s): Sentinel-1 ; ***Method(s):*** unsupervised classification, + thinning algorithm ; ***Message(s):*** Sentinel-based river network products were superior to the comparator data sets by a substantial margin

17. **Liu et al. (2022)** ***Fusing Landsat-8, Sentinel-1, and Sentinel-2 Data for River Water Mapping Using Multidimensional Weighted Fusion Method*** https://doi.org/10.1109/TGRS.2022.3187154
Sensor(s): Landsat-8, Sentinel-1, and Sentinel-2; ***Method(s):*** data fusion, water probability maps with SVM + multidimensional weighted fusion method (MDWFM); ***Message(s):*** fusion process not only improves the quality of river water mapping but also excludes the cloud interference; stable and accurate river extent mapping results obtained through fusing multiple images with high spatial resolution (SR) (10 m) and short revisit interval (0.4–4.4 days) are of great significance for enriching the data and methodology of hydrological studies.

18. Schmitt (2020) ***Potential of Large-Scale Inland Water Body Mapping from Sentinel-1/2 Data on the Example of Bavaria's Lakes and Rivers*** https://doi.org/10.1007/s41064-020-00111-2
Sensor(s): Sentinel-1, Sentinel-2; ***Method(s):*** Data fusion + SVM, MNDWI; ***Message(s):*** The main limitation arises from missed smaller water bodies, which are not observed in bands with

a resolution of about 20 m. Given the simplicity of the proposed approach and the open availability of the Sentinel data, the study confirms the potential for a fully automatic large-scale mapping of inland water with cloud-based remote sensing techniques; Better accuracy than GSWL on small river segments

19. Soman & Indu (2022) ***Sentinel-1 based Inland water dynamics Mapping System (SIMS)*** **https://doi.org/10.1016/j.envsoft.2022.105305**
Sensor(s): Sentinel-1; ***Method(s):*** open-source code on GEE ; ***Message(s):*** Backend algorithm involves a novel framework configurable for rivers and lakes; Derived outputs can be exported as time series of surface water extent shapefiles.

20. Bioresita et al. (2018) ***A Method for Automatic and Rapid Mapping of Water Surfaces from Sentinel-1 Imagery*** **https://doi.org/10.3390/rs10020217**
Sensor(s): Sentinel-1; ***Method(s):*** Flood detection, automatic chain processing for surface waters extraction, Split-Based Approach (SBA), Finite Mixture Models (FMM); ***Message(s):*** Using Sentinel-1 as free SAR data with wide area monitoring capabilities, we established a processing chain which can extract floods and surface water areas automatically.

21. Du et al. (2012) ***Estimating Surface Water Area Changes Using Time-Series Landsat Data in the Qingjiang River Basin, China*** **https://doi.org/10.1117/1.JRS.6.063609**
Sensor(s): Landsat ; ***Method(s):*** NDWI, MNDWI; ***Message(s):*** useful for monitoring increase of surface water

22. Feyisa et la. (2014) ***Automated Water Extraction Index: A New Technique for Surface Water Mapping Using Landsat Imagery*** **https://doi.org/10.1016/j.rse.2013.08.029**
Sensor(s): Landsat ; ***Method(s):*** Automated Water Extraction Index (AWEI), classification; ***Message(s):*** devise an index that consistently improves water extraction accuracy in the presence of various sorts of environmental noise and at the same time offers a stable threshold value; classification accuracy of AWEI was significantly higher than that of MNDWI,; fairly stable optimal threshold for accurate classification; WEI can be used for extracting water with high accuracy, especially in mountainous areas where deep shadow caused by the terrain is an important source of classification error.

23. Huang et al. (2018) ***Detecting, Extracting, and Monitoring Surface Water from Space Using Optical Sensors: A Review*** **https://doi.org/10.1029/2018RG000598**
Sensor(s): Multiple; ***Method(s):*** Review ; ***Message(s):*** Satellite-based optical sensors are an efficient means for observing surface water regionally and globally; Pixel unmixing and reconstruction, and spatio-temporal fusion are two common and low-cost approaches to enhance surface water monitoring; The potential to estimate flow using only optical remote sensing has greatly enriched the data source of hydrological studies; The development of big data and cloud computation techniques makes the increasing demand of monitoring global

water dynamics at high resolutions easier to achieve; An integrated use of multisource data is the future direction for improved global and regional water monitoring.

24. Isikdogan et al. (2017) ***Surface Water Mapping by Deep Learning*** **https://doi.org/10.1109/JSTARS.2017.2735443**
Sensor(s): Landsat; ***Method(s):*** Convolutional Neural Network; ***Message(s):*** The trained model separates water from land, snow, ice, clouds, and shadows using only Landsat bands as input. Our code and trained models are publicly available at http://live.ece.utexas.edu/research/deepwatermap/; excellent accuracy even for smaller bodies

25. Rokni et al. (2014) ***Water Feature Extraction and Change Detection Using Multitemporal Landsat Imagery*** **https://doi.org/10.3390/rs6054173**
Sensor(s): Landsat; ***Method(s):*** Normalized Difference Water Index (NDWI), Modified NDWI (MNDWI), Normalized Difference Moisture Index (NDMI), Water Ratio Index (WRI), Normalized Difference Vegetation Index (NDVI), and Automated Water Extraction Index (AWEI); ***Message(s):*** NDWI was found superior to other indexes and hence it was used to model the spatiotemporal changes of the lake; approach based on Principal Components of multi-temporal NDWI (NDWI-PCs) was proposed and evaluated for surface water change detection.

26. Wang et al. (2018) A Robust Multi-Band Water Index (MBWI) for Automated Extraction of Surface Water from Landsat 8 OLI Imagery https://doi.org/10.1016/j.jag.2018.01.018
Sensor(s): Landsat; ***Method(s):*** Multi-Band Water Index (MBWI) + K-means cluster; ***Message(s):*** Compared with other water indices, the MBWI results in lower mean water total errors; robustly discriminating surface water from confused backgrounds that are usually sources of surface water extraction errors, e.g., mountainous shadows and dark built-up areas; able to mitigate the seasonal and daily influences resulting from the variations of the solar condition.

27. Xu (2006) ***Modification of Normalised Difference Water Index (NDWI) to Enhance Open Water Features in Remotely Sensed Imagery*** **https://doi.org/10.1080/01431160600589179**
Sensor(s): Landsat ; ***Method(s):*** MNDWI ; ***Message(s):*** MNDWI is more suitable for enhancing and extracting water information for a water region with a background dominated by built-up land areas because of its advantage in reducing and even removing built-up land noise over the NDWI.

28. Yu et al. (2016) ***Convolutional Neural Networks for Water Body Extraction from Landsat Imagery*** **https://doi.org/10.1142/S1469026817500018**
Sensor(s): Landsat; ***Method(s):*** CNN; ***Message(s):*** proposed model achieves better performance than support vector machine (SVM) and artificial neural network (ANN)

29. **Allen et al. (2020) Timing of Landsat Overpasses Effectively Captures Flow Conditions of Large Rivers https://doi.org/10.3390/rs12091510**
Sensor(s): Landsat; ***Method(s):*** N/A; ***Message(s):*** Landsat archive is, on average, representative of the temporal frequencies of hydrological conditions present along Earth's large rivers with broad utility for hydrological, ecologic and biogeochemical evaluations of river systems

30. **Walker et al. (2020) Integrating stream gage data and Landsat imagery to complete time-series of surface water extents in Central Valley, California https://doi.org/10.1016/j.jag.2019.101973**
Sensor(s): Landsat; ***Method(s):*** data fusion with in-situ measurements ; ***Message(s):*** generated continuous time series of 30+ years in 35 HUCs, demonstrating that this technique can provide quantitative estimates of historical surface water extents and elucidate flooding or drought events over the period of data collection

31. **Huang et al. (2018) Automated extraction of surface water extent from Sentinel-1 data https://doi.org/10.3390/rs10050797**
Sensor(s): Sentinel-1; ***Method(s):*** Automatic extraction based on AI classification; ***Message(s):*** fully automated algorithms were developed to derive water probability and classified maps of water and non-water is achievable.

32. **Shen et al. (2022) Water Body Mapping Using Long Time Series Sentinel-1 SAR Data in Poyang Lake https://doi.org/10.3390/w14121902**
Sensor(s): Sentinel-1; ***Method(s):*** modified U-Net convolutional neural network classification,; ***Message(s):*** Sentinel-1 SAR and WaterUNet are very suitable for water body monitoring as well as emergency flood mapping

33. **Niroumand-Jadidi (2016) *OPTIMAL BAND RATIO ANALYSIS OF WORLDVIEW-3 IMAGERY FOR BATHYMETRY OF SHALLOW RIVERS (CASE STUDY: SARCA RIVER, ITALY)***
https://pdfs.semanticscholar.org/46d8/69f5f2271d512d5c9c36776e818083f4dda2.pdf
Sensor(s): WorldView-3, GeoEye; ***Method(s):*** Optimal Band Ratio Analysis (OBRA), Bathymetry; ***Message(s):*** effect of changes in water depth is highly pronounced in longer wavelengths (i.e. NIR) due to high and rapid absorption of light in this spectrum as long as it is not saturated.

34. **Figorito et al. (2012) *An object-based method for mapping ephemeral river areas from WorldView-2 satellite data* https://doi.org/10.1117/12.974689**
Sensor(s): WorldView-2; ***Method(s):*** object-based classification; ***Message(s):*** allow acquiring detailed basic information on an ephemeral river area

35. **Lu et al. (2021) *High-resolution satellite-derived river network map reveals small Arctic river hydrography* https://doi.org/10.1088/1748-9326/abf463**

Sensor(s): Sentinel-2; ***Method(s):*** Data fusion with DEM; ***Message(s):*** Quantified the river hydrography (stream order and river width, length,surface area, velocity, slope, sinuosity, and catchment area); ydrography to a 10-m spatial resolution and raise prospects for tracking dynamic surface water processes with high-resolution satellite observations.

36. Wolf (2012) ***Using WorldView 2 Vis-NIR MSI Imagery to Support Land Mapping and Feature Extraction Using Normalized Difference Index Ratios*** **https://doi.org/10.1117/12.917717**
Sensor(s): WorldView-2; ***Method(s):*** supervised classification; ***Message(s):*** suitable for fine scale land mapping

37. Legleiter (2012) ***MAPPING RIVER DEPTH FROM PUBLICLY AVAILABLE AERIAL IMAGES*** **https://doi.org/10.1002/rra.2560**
Sensor(s): Aerial imagery; ***Method(s):*** flow depths estimation; band ratio-based algorithm; ***Message(s):*** Comparison of remotely sensed bathymetric maps with field surveys indicated that although the locations of pools were determined accurately; Although a number of other constraints also must be considered, such as the need for local calibration data, depth retrieval from publicly available image data is feasible under appropriate conditions.

38. Flener et al. (2013) ***Seamless Mapping of River Channels at High Resolution Using Mobile LiDAR and UAV-Photography*** **https://doi.org/10.3390/rs5126382**
Sensor(s): LiDAR, UAV; ***Method(s):*** creating high-resolution seamless digital terrain models (DTM) of river channels and their floodplains.; ***Message(s):*** useful but restricted for small areas

39. Vericat et al. (2008) ***Accuracy assessment of aerial photographs acquired using lighter-than-air blimps: low-cost tools for mapping river corridors*** **https://doi.org/10.1002/rra.1198**
Sensor(s): UAV; ***Method(s):*** accuracy assessment; ***Message(s):*** cost-effective alternative to traditionally commissioned flights

40. Marcus & Fonstad (2007) ***Optical remote mapping of rivers at sub-meter resolutions and watershed extents*** **https://doi.org/10.1002/esp.1637**
Sensor(s): IKONOS; ***Method(s):*** Data fusion satellite with different image types (radar, lidar, thermal); ***Message(s):*** The greatest obstacle to development and implementation of more remote sensing, catchment scale 'river observatories' is the absence of broadly based funding initiatives to support collaborative research by multiple investigators in different river settings.

41. Yang and Chen (2017) ***Evaluation of automated urban surface water extraction from Sentinel-2A imagery using different water indices*** **https://doi.org/10.1117/1.JRS.11.026016**
Sensor(s): Sentinel-2; ***Method(s):*** MNDWI; automated water extraction index (AWEI); ***Message(s):*** good for small rivers

42. Raza et al. (2021) *Drought Prediction with Raw Satellite Imagery and Ensemble Supervised Machine Learning* **https://doi.org/10.18488/journal.80.2021.81.1.7**
Sensor(s): - ; **Method(s):** Boosting and bagging -> ensemble supervised machine learning techniques. **Message(s):** Drought prediction can be made considering vegetation and water level in any region, therefore use raw satellite images and ML to predict drought conditions and its various stages -> detect if the images show: drought, pre-drought, post drought or no drought conditions. Bagging proven to perform better and less computationally expensive than boosting method.
43. Prodhan, F.A.; Zhang, J.; et al. (2021). *Deep Learning for Monitoring Agricultural Drought in South Asia Using Remote Sensing Data,* **https://doi.org/10.3390/rs13091715**
Sensor(s): MODIS + ground observations; **Method(s):** Monitor drought using deep learning with remote sensing data and ground observations from weather stations, in South Asia, from 2001 - 2016. **Message(s):** Precipitation, vegetation, and soil factors are considered as inputs for a Deep Forward Neural Network (DFNN) and the soil moisture deficit index (SMDI) as a response variable to evaluate agricultural drought. The results of the deep learning model were also analysed in comparison with two machine learning models, distributed random forest (DRF) and gradient boosting machine (GBM), with a measured outperformance by the DFNN model.

Applications review

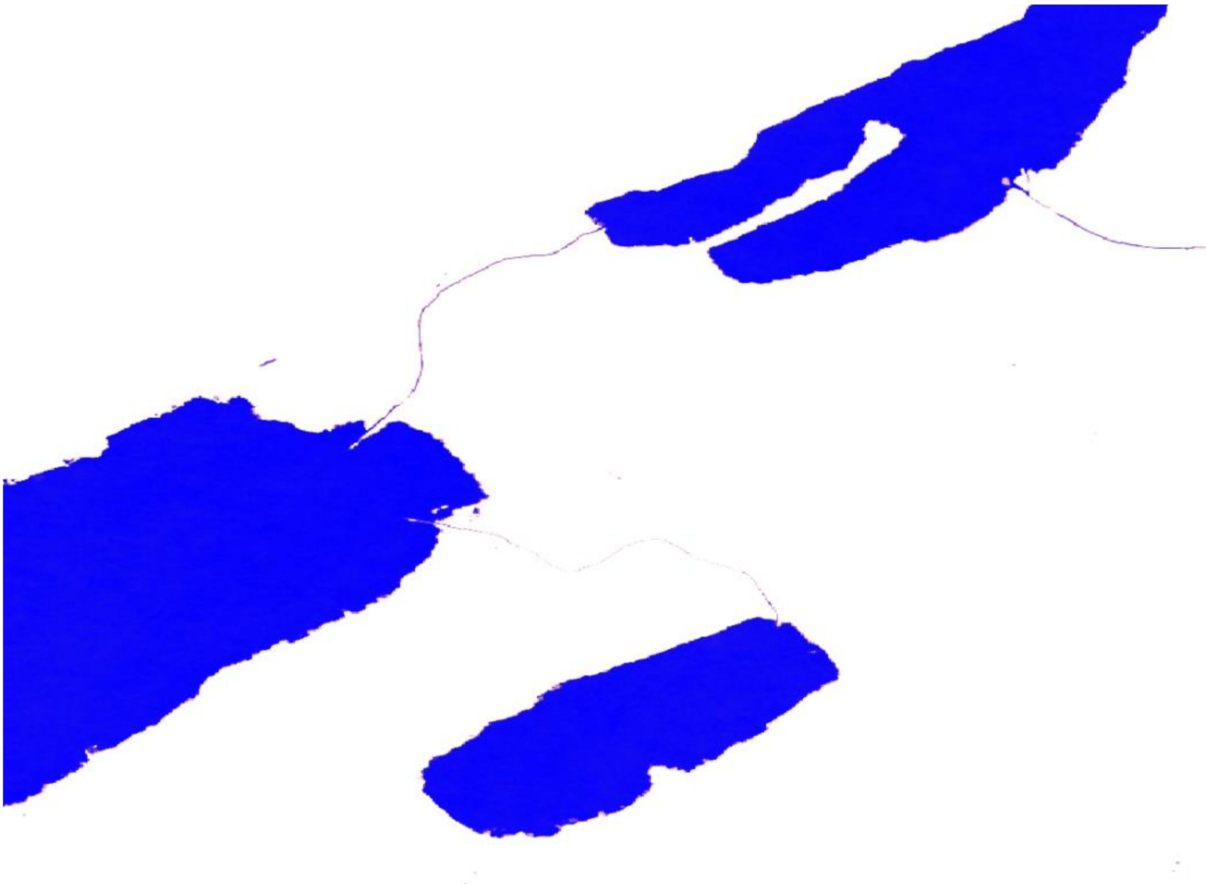
Freshwater Ecosystems Explorer - SDG6.6.1
URL: https://www.sdg661.app
Short Description: The Freshwater Ecosystems Explorer is a free and easy to use data platform. It provides accurate, up-to-date, high-resolution geospatial data depicting the extent freshwater ecosystems change over time. Data can be visualized and downloaded at national, sub-national and basin levels. Data is available for the following: Permanent & Seasonal Surface Waters | Reservoirs | Wetlands | Mangroves | Water Quality
Sensors: Landsat
Article(s): https://files.habitatseven.com/unwater/SDG-Monitoring-Methodology-for-Indicator-6.6.1.pdf

- ***Benefits:*** Methodology well established following international standards; time-series data;
- ***Limitations:*** Only able to detect major watercourses

Global Surface Water Explorer
URL: https://global-surface-water.appspot.com
Short Description: This tool is the one that is providing the content of the previous application.
Sensors: Landsat
Article(s): https://doi.org/10.1038/nature20584

- ***Benefits:*** Same as **Freshwater Ecosystems Explorer - SDG6.6.1**
- ***Limitations:*** Same as **Freshwater Ecosystems Explorer - SDG6.6.1**

The figure below (region between Neuchatel, Bienne and Morat Lakes) highlight how only the large rivers can be monitored with medium resolution imagery.



Copernicus Global Land Service - Water Level
URL: https://land.copernicus.eu/global/products/wl
Short Description: https://land.copernicus.eu/global/products/wl
Sensors: Altimeter
Article(s): N/A

- ***Benefits:*** Methodology freely available, can be a good complement to access in-situ data
- ***Limitations:*** No data available for Switzerland

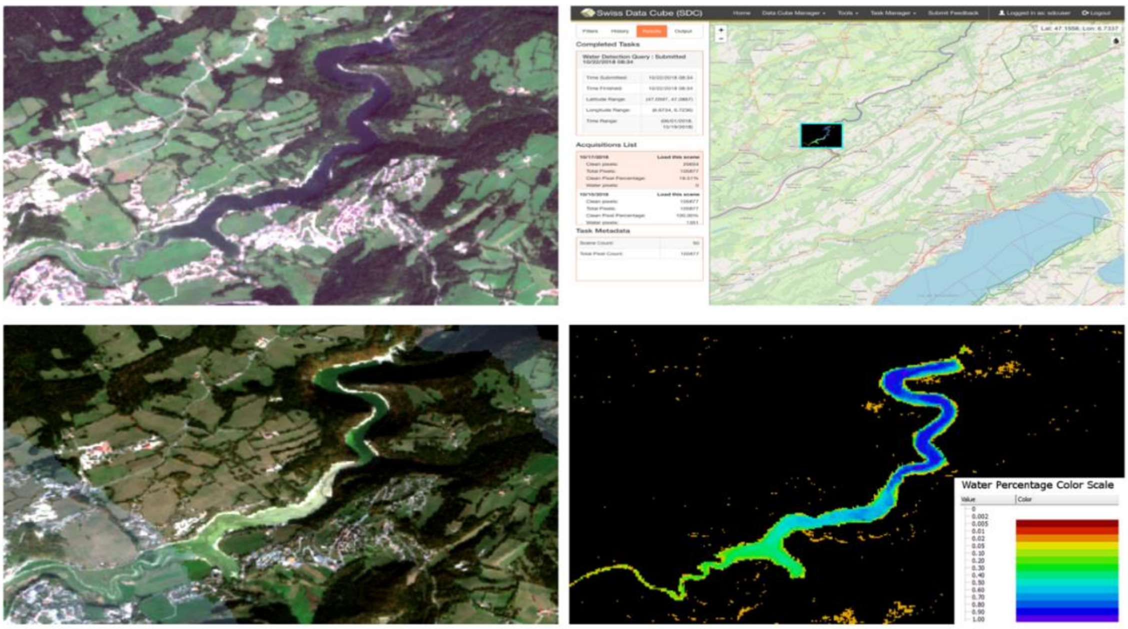
Copernicus Pan-European Land Monitoring Service - Water & Wetness
URL: https://land.copernicus.eu/pan-european/high-resolution-layers/water-wetness
Short Description: https://land.copernicus.eu/pan-european/high-resolution-layers/water-wetness
Sensors: Sentinel-1
Article(s): https://land.copernicus.eu/pan-european/high-resolution-layers/water-wetness/resolveuid/e6986e188aca449ab3a23dba4a315782

- ***Benefits:*** High-resolution (10m), SAR,
- ***Limitations:*** Only two years, only major rivers detected

Water Observations from Space (WOfS)
URL: https://www.dea.ga.gov.au/products/dea-water-observations
Short Description: uses an algorithm to classify each pixel from Landsat and Sentinel satellite imagery as 'wet', 'dry' or 'invalid'. Combining the classified pixels into summaries, covering a year, season, or all of time (since 1987) gives the information on where water is usually, and where it is rarely.
Sensors: Landsat, Sentinel-2
Article(s): https://doi.org/10.1016/j.rse.2015.11.003

- ***Benefits:*** Can be applied to different sensors; time-series; can really beneficial in term of monitoring
- ***Limitations:*** never tested on VHR data

Example: Lake des Brenets



Sentinel-2 True Color Mosaic - 2018 (bottom) vs 2017 (top)　　Water detection – 2018 [June-October]

European Drought Monitoring Service
URL: https://edo.jrc.ec.europa.eu/edov2/php/index.php?id=1000
They have a Low Flow Index from 2020-2022 and more generally are providing interesting information on Land Conditions during Droughts.

Dynamic Surface Water Extent
URL: https://www.usgs.gov/landsat-missions/landsat-dynamic-surface-water-extent-science-products
Available only for the US, Alaska and Hawaii
Based on Landsat
Consider only major rivers

Drought Watch (https://wandb.ai/site/articles/droughtwatch) is a project aiming to improve drought detection using deep learning and satellite images. The project is part of the Weights & Biases Benchmarks (https://github.com/wandb/droughtwatch), which offers a centralised platform for open collaboration of deep learning projects. The prediction of drought conditions is done by learning a mapping from satellite images to forage quality, based on a dataset of 100’000 satellite images in North Kenya and manual labels of forage quality at corresponding geolocations.

Activity 2

Potential data sources:

resolution	**sensor**	**m**	**time_range**	**actual frequency**	**Bands**	**advantage**	**limitations**
medium	Landsat 4,5,7,8,9	30	1984 - ongoing	8 days / 2	R, G, B, NiR, SWIR1, SWIR2	many bands time range frequency	optic (cloud) resolution
medium	Sentinel 2	10	2015 - ongoing	5 days / 2	R, G, B, NiR, SWIR1, SWIR2, VEG5, VEG6, VEG7	many bands frequency resolution	optic (cloud) resolution
medium	Sentinel 1	10	2014 - ongoing	12 days / 2	hh, hv	radar	resolution downsampling probably required
High	WorldView 2-4	1.84 - 1.24 (MS)	2009 - ongoing	4.5 days	8 bands	many_bands resolution frequency	not free optic (cloud)
high	GeoEye 1	0.4	??	on order	R, G, B, NiR	resolution	not free frequency optic (cloud) bands
very high	Aerial View	0.25	??	on request	R, G, B	resolution	not free frequency optic (cloud) bands
very high	LiDAR flight	selectable	on request	on request	??	radar resolution	not free frequency

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Similar table in Huang et al. 2018a:

Table 1
Commonly Used Spaceborne Remote Sensors for Surface Water Detection Listed by Group[a]

Sensor group	Satellite/sensor	Number of bands	Spatial resolution (m)	Temporal resolution (day)	Maximum swath at nadir (km)	Scale of application[b]	Data distribution policy (costs)	Data availability
Coarse resolution sensor	NOAA/AVHRR	5	1,100	0.5	2,800	R-G	no	1978--
	MODIS	36	250–1,000	0.5	2,330	R-G	no	1999--
	Suomi NPP-VIIRS	22	375–750	0.5	3,040	R-G	no	2012--
	MERIS	15	300	3	1,150	R-G	no	2002-2012
	Sentinel-3 OLCI	21	300	2	1,270	R-G	no	2016--
Medium resolution sensor	Landsat	4–9	15–80	16	185	L-G	no	1972--
	SPOT	4–5	2.5–20	26	120	L-R	yes	1986--
	Aster	14	15–90	16	60	L-G	no	1999--
	Sentinel-2 MSI	13	10–60	5	290	L-R	no	2015--
High resolution sensor	IKONOS	5	1–4	1.5–3	11.3	L-R	yes	1999--
	QuickBird	5	0.61–2.24	2.7	16.5	L	yes	2001--
	WorldView	4–17	0.31–2.40	1–4	17.6	L	yes	2007--
	RapidEye	5	5	1–5.5	77	L-R	yes	2008--
	ZY-3	4	2.1–5.8	5	50	L-R	yes	2012--
	GF-1/GF-2	5	1–16	4–5	800	L-R	yes	2013--

[a]The spatial resolution, temporal resolution, and spectral resolution (number of bands) vary among sensors. The area coverage (swath) determines the scale of application and also varies among sensors. [b]L, landscape; R, regional; G, global; L-R, landscape to regional; L-G, landscape to global; R-G, regional to global.

- LiDAR: Flener et al. (2013)

Optical indices:

The table below summarise potential water indices based of literature review and https://github.com/awesome-spectral-indices/awesome-spectral-indices

short_name	long_name	B	G	R	N	S1	S2	T1
AWEInsh	Automated Water Extraction Index		x		x	x	x	
AWEIsh	Automated Water Extraction Index with Shadows Elimination	x	x		x	x	x	
HRWI	High REsolution Water Index		x	x	x			
LSWI	Land Surface Water Index				x	x		
MBWI	Multi-Band Water Index		x	x	x	x	x	
MLSWI26	Modified Land Surface Water Index (MODIS Bands 2 and 6)				x	x		
MLSWI27	Modified Land Surface Water Index (MODIS Bands 2 and 7)				x		x	
MNDWI	Modified Normalized Difference Water Index		x			x		
MuWIR	Revised Multi-Spectral Water Index	x	x		x	x	x	
NDMI	Normalized Difference Moisture Index				x	x		
NDVIMNDWI	NDVI-MNDWI Model		x	x	x	x		
NDWI	Normalized Difference Water Index		x		x			
NDWIns	Normalized Difference Water Index with no Snow Cover and Glaciers		x		x			
NWI	New Water Index	x			x	x	x	
RNDWI	Revised Normalized Differential Water Index			x			x	

SWM	Sentinel Water Mask	x	x		x	x		
WI1	Water Index 1		x				x	
WI2	Water Index 2	x					x	
WI2015	Water Index 2015		x	x	x	x	x	
WRI	Water Ratio Index		x	x	x	x		
TCW	Tasseled Cap Wetness	x	x	x	x	x	x	

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- **B**lue, **G**reen, **R**ed, **N**iR, **S**WIR**1**, **S**WIR**2**, **T**hermal**1**
- Bands columns in white (R, G, B) are the bands available for all optic sensors.

Columns in red are the band not available in Aerial View or GeoEye.
Column in red is the band not available in Aerial View sensors.

- No indices can be computed for Aerial View.
- NDWI, NDWIlns and HRWI are the only indices which can be computed for all sensors (except Aerial View).
- Notice how the thermal band is never used.

The table below summarises how often indices are used in the publication in reference of this report.

Reference	**NDWI**	**MNDWI**	**AWEInsh**	**AWEIsh**	**TCW**	**WI2015**	**RMNDWI**	**LSWI**	**NDMI**	**WRI**	**MBWI**	**HRWI**
Bioresita et al. (2019)	x											
Du et al. (2012)	x	x										
Feyisa et al. (2014)		x	x	x								
Huang et al. (2018)	x	x	x		x	x						
Kulkarni et al. (2022)	x	x	x	x								
Li et al. (2020)		x		x			x					
Li et al. (2021)	x	x										

Obida et al. (2019)	x	x						x				
Ogilvie et al. (2018)		x										
Rokni et al. (2014)	x	x							x	x		
Schmitt (2020)		x										
Soman & Indu (2022)		x										
Thissen (2019)	x	x	x		x	x						
Tian et al. (2020)	x	x	x	x								
Walker et al. (2020)		x	x	x								
Wang et al. (2018)	x	x									x	
Wieland & Martinis (2020)	x	x	x	x		x					x	x
Wolf (2012)	x											
Xu (2006)	x	x										
Yang & Chen (2017)		x										
Yao et al. (2015)	x											x
	14	18	7	6	2	3	1	1	1	1	2	2

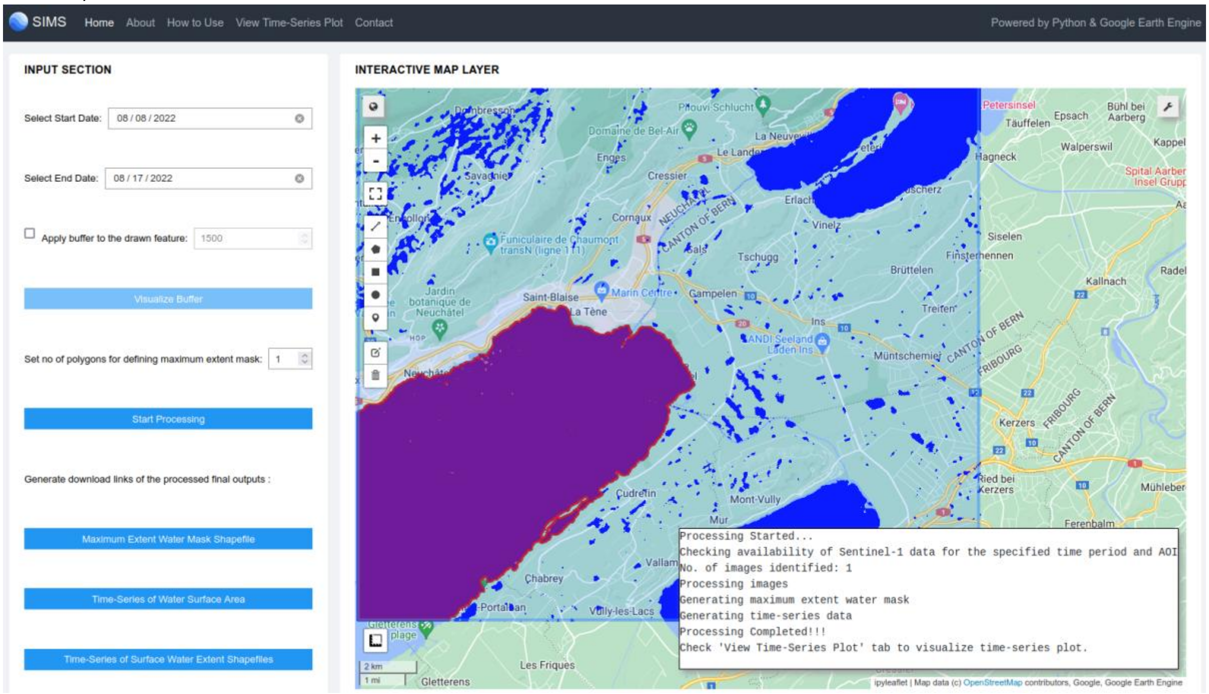
File: https://docs.google.com/spreadsheets/d/1K_MzSHvBdbZ1BnSJF77pUFPcMk76fLPn0lR93XgogqI/edit?usp=sharing

Modified Normalized Difference Water Index (MNDWI) is by far the most common indicator, followed closely by Normalized Difference Water Index (MNDI) and Automated Water Extraction Index (AWEI) indices.

"It is now widely accepted that mNDWI is more stable and reliable than NDWI, because the SWIR band is less sensitive to concentrations of sediments and other optical active constituents within the water than the NIR band is" (Huang et al. (2018))

Active Indices

Synthetic Aperture Radar (SAR) sensors such as Sentinel-1 are frequently used to detect or monitor water bodies (Shen et al. (2022), Schmitt (2020), Obida et al. (2019)).
Soman & Indu (2022) developed the Sentinel-1 based Inland water dynamics Mapping System (SIMS) in India, the SIMS code is available in https://github.com/manuks481/SIMS-WebApp, and as a web app in https://sims-toolkit.herokuapp.com. But as it can be seen in the figure below, result is far to be accurate.



Tian et al. (2020) proposed the Sentinel-1 Water Index (SWI) based on a linear combination of the VV- and VH- polarization images and illustrated that SWI could more reliably identify water bodies than the traditional threshold method that directly uses VV- and/or VH-polarization imagery.

2.3. *Sentinel-1 Water Extraction Model*

Our previous study [4] proposed a simple but robust SWI-based water extraction model (SWIM) derived from Sentinel-1 imagery to extract the spatial distribution of water areas. The SWI was computed as:

$$SWI = 0.1747 \times \beta_{vv} + 0.0082 \times \beta_{vh} \times \beta_{vv} + 0.0023 \times {\beta_{vv}}^2 - 0.0015 \times {\beta_{vh}}^2 + 0.1904 \quad (3)$$

where β_{vh} and β_{vv} represent the backscattering coefficients in for VH and VV polarization, respectively. Based on our previous results, if the SWI value of one pixel is more than 0.2, it is regarded as a water body [4]. The specific codes of SWIM on GEE are as shown in Appendix A.

Tian et al. (2020) code is available at https://code.earthengine.google.com/da1544aef0d6ca84df9d388611549e73

Other methods

- Li et al. 2021: "K-T transformation (also called Tasseled cap transformation) is a special principal component analysis (PCA)... the third component wetness reflects the humidity information of ground objects. The wetness component is the most sensitive to soil wetness information and it is a better characteristic band for water information extraction."
- Ijaz et al. (2018): "Supervised classification with the maximum likelihood algorithm performed better for OLI imagery (30 m) than high spatial resolution RapidEye (5 m) imagery. However, unsupervised classification method was not suitable due to the significant overlapping of interand intra-class pixels."
- SVM/CNN:

"Since the idea of deep learning was proposed by Geoffrey Hinton in 2006, deep learning has attracted more and more attention, and deep Convolutional Neural Network (CNNs) has also shown advantages in the field of image semantic segmentation. As commonly used models in deep learning, CNNs have become tremendously popular in recent years because CNNs can learn extremely complicated hierarchical features from massive amounts of data, greatly reduce the number of parameters, enhance the generalization ability, and realize the qualitative task of image recognition" (Shen et al. (2022))

"Traditional Landsat water indices require carefully selected threshold values that vary depending on the region being imaged and on the atmospheric conditions. They also suffer from many false positives, arising mainly from snow and ice, and from terrain and cloud shadows being mistaken for water. Systems that produce high-quality water maps usually rely on ancillary data and complex rule-based expert systems to overcome these problems. Here, we instead adopt a data-driven, deep learning-based approach to surface water mapping. We propose a fully convolutional neural network that is trained to segment water on Landsat imagery. Our proposed model, named DeepWaterMap, learns the characteristics of water bodies from data drawn from across the globe. The trained model separates water from land, snow, ice, clouds, and shadows using only Landsat bands as input. Our code and trained models are publicly available at http://live.ece.utexas.edu/research/deepwatermap/" (Isikdogan et al. (2017)). And the related code is available in https://github.com/isikdogan/deepwatermap seems to be easily useable with SDC products.

"The optimal coefficients of the HRWI formula was determined using Support Vector Machine (SVM). The SVM is a non-parametric statistical learning technique, which is also a large-margin classifier. Its motivation is to find the best hyperplane which represents the largest separation between two class types." (Wieland & Martinis (2020))
CNN was also used by Wieland & Martinis (2020), or Yu et al. (2017)

- Fusion / pan-sharpening:

Liu et al. (2022) fused optic and SAR sensors (Landsat 8, Sentinel 1 and Sentinel 2).
Schmitt (2020) combined Sentinel 1 and 2.
Vanderhoof & Lane (2019) pan-sharpened Worldview-2, QuickBird-2 and GeoEye-1.

- unmanned aerial vehicle (UAV) were also used by Flener et al. (2013) in combination with Light Detection and Ranging/Laser scanning (LiDAR). Or Vericat et al. (2009) who tested several "lighter-than-air blimps" for mapping river corridors. Such technology been only valid for small geographical extent.
- Water connectivity is an issue which can easily be fixed by buffering and shrinking water mask (Li et al. (2020), figure below)

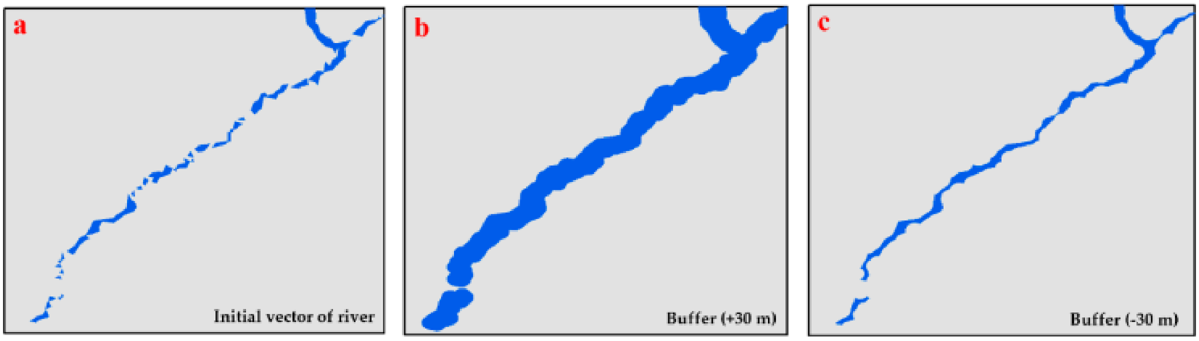


Figure 5. Connectivity processing of disconnected rivers. (**a**) Disconnected river extraction from Sentinel-2 images; (**b**) buffering result of 30 m of outward expanding of (**a**); (**c**) buffering result of 30 m inward contracting of (**b**).

- Using Digital Elevation Model (DEM) as auxiliary data allows to simply restrict detected water bodies to "flat" areas, or use mora advanced Height Above the Nearest Drainage (HAND) like in Lu et al. (2021), Bioresita et al. (2019), Thissen (2019), Bioresita et al. (2018).

Swiss Data Cube potential

- SDC contains by default a selection of official products (Landsat 4,5,7,8 and 9, Sentinel 2) containing the full collection if imagery freely accessible. In the context of this project "punctual" products were added (sur as selection of Geoeye and Aerila view scene. For which the access is restricted to authorised users.
- Once punctual data indexed in SDC as a product, it allows to process them using the same scripts as other available products (as long as they all contains similar bands required for the processing).
- Even if high resolution imagery is generally available only for a few dates (contrarily to default SDC medium resolution products with return periods of a few days), processing them requires huge computing resources (e.g. one scene of Aerial View at 0.25 cm

resolution requires 14,400 time more resource then a Landsat scene at 30 m resolution ((30 / 0.25)^2).
- Open Data Cube (ODC) function Water Observation from Space (WOfS, Mueller et al. 2016) “provides insight into the behaviour of surface wate … through time”, but it requires bands blue, green, red, nir, swir1 and swir2, which makes WOfS methodology impossible in optical imagery as GeoEye and Aerial View (Swissimage and Swissimage RS).

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Activity 2

Compilation of available imagery data (SWISSIMAGE as priority data set) with sufficiently high spatial resolution during drought events (e.g., 2003, 2011, 2015, and 2018) of potentially affected stream segments and creation of a reference dataset to compare dry vs. normal conditions.

<u>Expected results:</u> A compilation of available (very-) high images of affected rivers & a reference dataset for comparison with "normal" conditions. This will serve as the basis for the decision whether to proceed with activity 3.

<u>Objective of the project:</u> Potential of remote sensing data and other methods to collect information during drought such as location of dry watercourse section.

1. SWISSIMAGE

- Partially available RGB til 2017 in UNIGE server, access requested to Thierry Froidevaux, but waiting for answer (sftp access impossible to not broke SITG workflow).
- RGBNiR request made to SWiss Topo through Thierry Froidevaux, but too big according to swisstopo, then QuickOthoPhoto AOI requested fro years 2018, 2021.

2. Special flight swisstopo

- RapidMapping downloaded, and final product received via HD from swisstopo. RapidMapping superseded by final product who was indexed on SDC v2

3. GeoEye

- One dataset received and indexed on SDC v2

4. Landsat

- Ready to go on SDC v2

5. Sentinel-1

- Not available in SDC v1, and no source nor workflow identified for SDC v2

6. Sentinel-2

- First part of workflow (AWSL2) ready to get SDC v2 data, waiting for storage.
- In the meanwhile 1 scene (12.8.2022) downloaded (to be indexed if full collection not available when indice calculation will be done)

GE “reference” dataset creation

1. Unsupervised classification performed within the SDC with Jupyter script *0_HR_auto_classif.ipynb* (available in zipped annex provided with this document in the *GE_classif subfolder*) using 36 chunks (to be able to run the script without filling the available memory. Which created 31 classified geotiff (as 5 chunks did not contain data).
2. Then the geotiffs were loaded in QGIS and water class of each of them was manually identified and extracted before to be merged and intersected with the riverbed layer (swissTMN3D_riverbed_aoi.gpkg also available in zipped annex).
3. Resulting raster was polygonised and features smaller than 1 m^2 were removed.
4. A virtual 1 km gris was created and intersected with the layer, then features smaller than 0.14 m^2 were removed. This chunking will later allow user to randomly select a given percentage of area classified as water as a training dataset.
5. Finally hole smaller than 5 m^2 were filled and the result (*GE_auto_water.gpkg* also available in zipped annex) imported into SDC to be used as training dataset in the supervised classification exploration phase.