Final Project Report

Integrated lake ice monitoring and generation of sustainable, reliable, long time series

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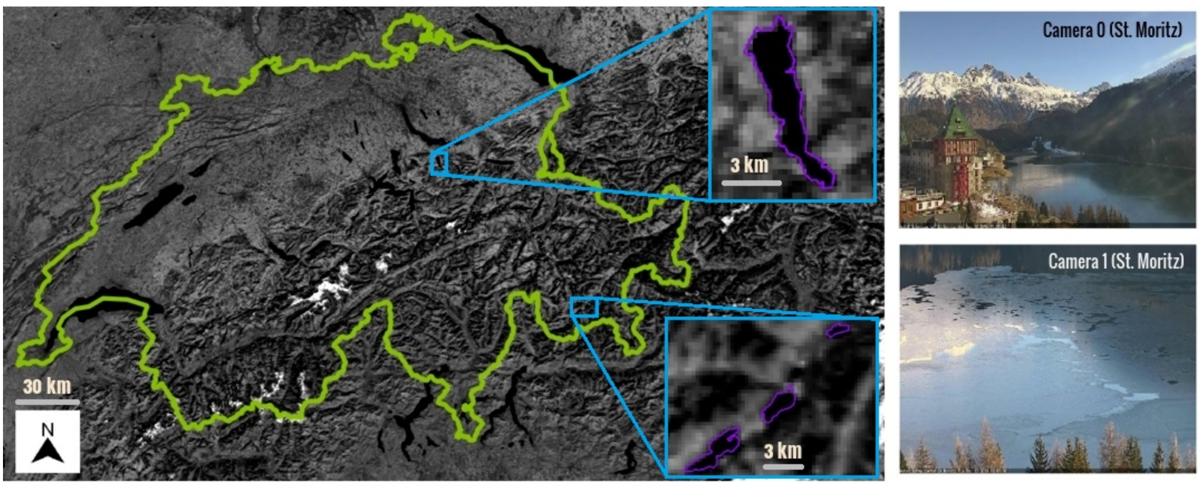


Zürich, October 2020

Summary

This project is related to the Global Climate Observing System (GCOS) Switzerland (CH), Call for Projects, Pillar 1 "Enhance and strengthen the Swiss climate observing system", Priority 1.3 "Promote the integration of existing and emerging observation methods". It is based on a finished project (Lake Ice Project, LIP) initiated by MeteoSwiss in the framework of GCOS CH "Integrated Monitoring of Ice in Selected Swiss Lakes" (Tom et al., 2019). It focuses on lake ice estimation over longer time periods but also methods that will enable a sustainable, reliable and long time series lake ice monitoring in the future. Lake ice, as part of the GCOS Essential Climate Variable (ECV) lakes, is an important factor (sentinel) for monitoring climate change and global warming. Since there are no systematic and reliable observations of lake ice in Switzerland in the past many years, we use various sensors and methodologies to operationally accomplish this.

Regarding sensors, we use satellites (secure, large-area and repetitive coverage) to monitor some carefully selected lakes in Switzerland. Apart from MODIS/VIIRS optical sensors (for VIIRS with expected future continuity from the National Aeronautics and Space Administration (NASA)), we use the free and seemingly of guaranteed continuity Sentinel-1 and -2 data from European Space Agency (ESA), at a much better spatial resolution than MODIS/VIIRS, able to monitor also small lakes. Of particular importance is the usage of Sentinel-1 Synthetic Aperture Radar (SAR) microwave data to reduce the grave problem of clouds in Switzerland and also errors in cloud masks for the optical sensors. We also use Webcam data, which are becoming increasingly (and freely) available and are much less affected by clouds and are better suited for monitoring of small lakes, that are imaged as few pixels in satellite images. They also can provide "ground truth" (reference data) after manual interpretation. Since current Webcams have a rather poor image quality, are placed arbitrarily (not optimised for lake monitoring) and are usually fixed, we use a new, better quality Webcam with Pan-Tilt-Zoom (PTZ) capabilities at lake St. Moritz. We also explore the possibilities of crowd-sourced lake images from the internet. A final platform/sensor that we use is Unpiloted Aerial Vehicles (UAVs) with an RGB camera, as a pilot project for lake ice but mainly possibly other climate and environmental applications and for validation of specific campaigns. Auxiliary data (especially temperature) from the meteorological stations close to the lakes can also provide support for better interpretation of the results. Our optical satellite-based method obtains mean Intersection-over-Union (mIoU) scores of > 83.9%, on both MODIS and VIIRS data. On average, our Webcam approach achieves mIoU values of ≈87%. Furthermore, using Sentinel-1 SAR data, the proposed model reaches mIoU scores of >90%.

In summary, we propose a future-oriented sustainable system for lake ice monitoring, using mainly optical and SAR satellite sensors and for small lakes Webcams, which together form a stable data source, providing through Webcams also reference data. In our processing, we use state-of-the-art machine (especially deep) learning methodologies.

1. Introduction

Motivation. Climate change is one of the main challenges for humanity today, and there is a great necessity to observe and understand the climate dynamics and quantify its past, present and future state. Lake observables such as ice duration, freeze-up and break-up dynamics etc. play an important role in understanding the local and global climate change and provide a good opportunity for long-term monitoring. Lake ice is depleting at an increasing pace due to global warming, however a comprehensive and large-scale assessment of lake ice loss is partly not using all existing and emerging methodologies and technologies/sensors. The reduced lake ice affects winter tourism, cold-water ecosystems, hydroelectric power generation, water transportation, freshwater fishing etc., which further emphasises the need to monitor lake ice in an efficient and repeatable manner. Lake ice is a part of GCOS ECV lakes. This project is part of the GCOS Switzerland Strategy (GCOS Switzerland Strategy 2017-2026, 2017) and supports the GCOS Implementation Needs (GCOS Implementation Plan, 2016).

Aims. Existing observations and data on lake ice from local authorities, fishermen, ice-skaters, police, internet media, publications etc. are not well documented. Additionally, there has been a significant decrease in the number of such field observations in the past two decades. At the same time, the potential of different remote sensing sensors has been demonstrated to measure the occurrence of lake ice. In this context, we note that for our target region of Switzerland, the database at the National Snow and Ice Data Centre (NSIDC) currently includes only the ice-on/off dates of very few Swiss lakes, and only until 2012. Given the need for automated, continuous monitoring of lake ice, our goal is to explore the potential of artificial intelligence to support an operational system. We aim towards a machine (especially deep) learning-based system which monitors selected Alpine lakes in Switzerland and detects the spatio-temporal extent of ice.

Brief overview of the work. Though satellite data is the best operational input for global coverage, close-range Webcam data can be very valuable in regions with large enough camera networks (including Switzerland). Firstly, we use low spatial resolution (250-1000 m) but high temporal resolution (1 day) multispectral satellite images from two optical satellite sensors (Suomi NPP VIIRS, Terra MODIS). Here, we tackle lake ice detection using Support Vector Machines (SVM), XGBoost and Random Forests. Additionally, we analyse the long time series of MODIS (20 winters) and VIIRS (8 winters) to support estimates of the long-term lake ice trends in Switzerland. To circumvent the problems due to clouds in optical satellite data analysis, we analyse the radar (Sentinel-1 SAR) data using Convolutional Neural Networks (CNNs). In order to improve the temporal resolution of the Sentinel-1 based approach, we also analyse the Sentinel-2 data using SVM and propose a combined monitoring system. Moreover, we investigate the potential of images from freely available Webcams (including the data from a Pan-Tilt-Zoom (PTZ) camera at lake St. Moritz) using CNNs, for independent estimation of lake ice. Additionally, we use Webcam data for validation of results from satellite data. We also make available a new benchmark dataset (*Photi-LakeIce* dataset) for Webcam-based data analysis. Furthermore, we apply the CNN pre-trained on this Webcam dataset on images uploaded to social media websites by citizens. Lastly, we fine tune the Webcam-based CNN on UAV images (RGB). Due to the limited extent of this report, we refer for more details to Prabha et al. (2020) and Tom et al. (2020a, 2020b). In these publications also references to relevant related work, which cannot be included here, can be found.

Study area, time periods, and input data. Based on the experience from the previous project with MeteoSwiss (Tom et al., 2019), the four target lakes are: Sihl, Sils, Silvaplana and St. Moritz. These lakes freeze always (or almost always), with variable area (very small to medium-sized), altitude (medium to high), and surrounding topography (flat/hilly to mountainous). For satellite images, the lake outlines are digitised from Open Street Map (OSM) and have an accuracy of ≈25-50m. For Webcams, our algorithm determines the lake outline, largely automatically. To assess the performance of our MODIS, VIIRS, Sentinel-1, Sentinel-2 and Webcam methodologies, the data from two full winters (2016-17 and 2017-18) are used, including the relatively short but challenging freeze-up and break-up periods. In each winter, we process all dates available from the beginning of September till end of May. In order to study the long-term trends, we also process MODIS and VIIRS data from all winters since 2000-01 and 2012-13 respectively, till winter 2019-2020. Additionally, we analyse the PTZ Webcam data from the winter 2018-19. The crowd-sourced images that we use are not time stamped. In addition, using UAVs, we collected data of lake Sils on five days during the break-up period (two and three days from April 2018 and May 2019 respectively). Though we analyse only two lakes (St. Moritz and Sihl) using Webcam data, we process all four target lakes using the optical and radar satellite data. As reference data, we mainly used manual interpretation of Webcam images. For difficult cases, we used multiple images per day, multiple cameras, and neighbouring days, while in some cases more than one operator interpreted the data. The major difficulty was in separating water from thin, transparent ice.

2. Methods

We use state-of-the-art machine (especially deep) learning approaches as the backbone for developing a multi-sensor-based lake ice monitoring system and propose separate methodologies for optical satellite data (VIIRS, MODIS, Sentinel-2), radar satellite data (Sentinel-1 SAR) and RGB image data (Webcams, including a PTZ camera, crowd-sourced images, UAV images).

Optical satellite data processing. In this project, we improve the existing LIP methodology (Tom et al., 2019) for MODIS and VIIRS data to reduce the training process. Additionally, multi-temporal analysis is performed, and two additional classifiers (Random Forest, XGBoost) are used for lake ice observation. As in LIP, we propose lake ice detection using optical satellites as a two class (*frozen, non-frozen*) semantic segmentation problem. The block diagram of the improved methodology for MODIS and VIIRS data processing is shown in Fig. 1. More details of our MODIS and VIIRS methodology (data analysed, ground truth, pre-processing steps, feature selection, hyper-parameter tuning etc.) can be found in Tom et al. (2020b). Additionally, we downloaded and pre-processed the Sentinel-2 data from the Google Earth Engine (GEE) platform and adapted the existing LIP methodology (SVM classification) for MODIS and VIIRS data to Sentinel-2 data. More details on the Sentinel-2 methodology can be found in Aguilar (2020).

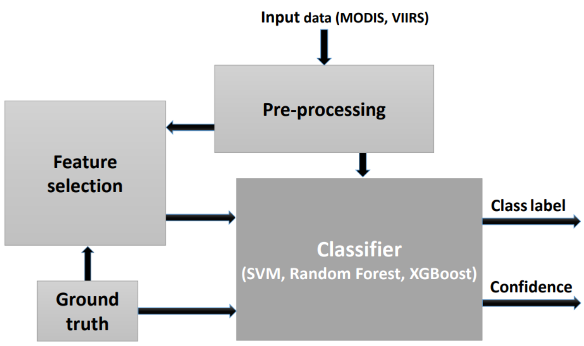
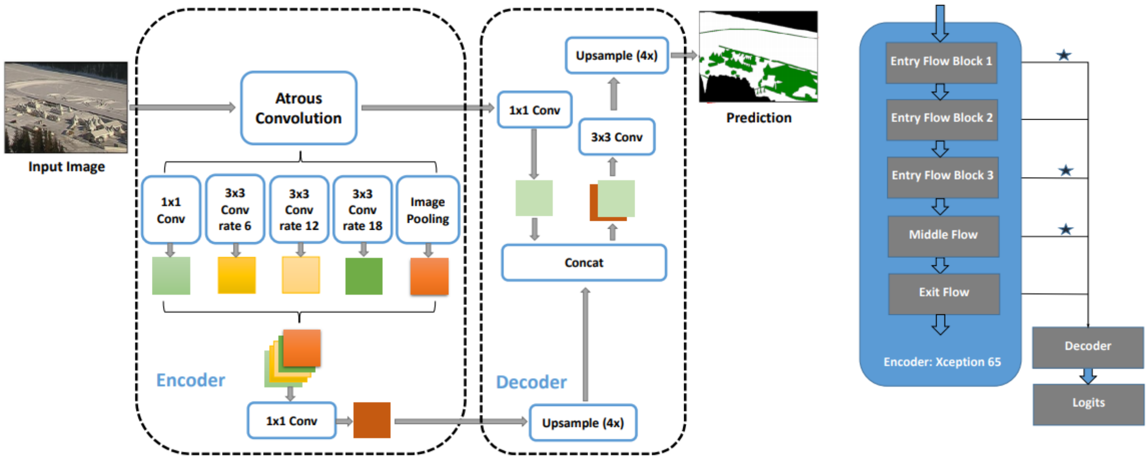


Figure 1. Block diagram of the methodology for optical satellite data. As opposed to MODIS and VIIRS, for Sentinel-2 processing we used only the SVM classifier and no feature selection was applied.

Radar satellite data processing. Frequent cloud cover is a main limiting factor when optical satellite imagery is used for lake ice monitoring. which we overcome thanks to the ability of microwave sensors to penetrate clouds and observe the lakes regardless of the weather and illumination conditions. We downloaded the ESA Sentinel-1 SAR data (level 1, GRD product, IW mode) and pre-processed it (border noise removal, thermal noise removal, radiometric calibration and terrain correction) in the GEE platform. The data thus received from GEE is further filtered by log-scaling to adapt the data distribution for CNNs. Using Sentinel-1 amplitude data, we cast ice detection as a two class (*frozen*, *non-frozen*) semantic segmentation problem and solve it using a state-of-the-art deep convolutional network (Deeplab v3+, Chen et al. (2018), see Fig. 2a). Though auxiliary data on temperature and wind are not used as an additional input to our CNN, such information is used to better interpret the results. For more details on the radar data processing methodology see Tom et al. (2020a) and Aguilar (2020).

Webcam (incl. a PTZ camera) and crowd-sourced image processing. We improve the existing Webcam-based lake ice monitoring algorithm (Tom et al., 2019) for lake ice detection (especially the generalisation performance across cameras and winters) with Deeplab v3+ CNN. Moreover, we design a variant of that model, termed *Deep-U-Lab* (see Fig. 2b), which predicts sharper, more correct segmentation boundaries. Additionally, we automate the lake detection step. Here, we model the lake detection as a two-class (*foreground, background*) pixelwise semantic segmentation problem and train another instance of the *Deep-U-Lab* segmentation model. For static Webcams, we run the lake detector on summer images, to sidestep the situation where both the lake and the surrounding ground is covered with snow. Once the lake mask is determined, the state of the lake is inferred using *Deep-U-Lab*. In this step, pixels are labelled as one of four classes (*water, ice, snow, clutter*). As part of the work, we introduce a new benchmark dataset of Webcam images, *Photi-LakeIce* (Prabha et al., 2020), from multiple cameras and two different winters, along with pixel-wise ground truth annotations (see Fig. 3 for some sample images). Additionally, we collected crowd-sourced lake images from the internet (Google search, Facebook, Instagram etc.) and used it for lake ice monitoring by fine tuning (transfer learning) a *Deep-U-Lab* model pre-trained on the *Photi-LakeIce* dataset. For more details on our Webcam and crowd-sourced data processing, see Prabha et al. (2020) and Prabha (2019). We also processed the images captured using a PTZ Webcam and compared it with the freely available Webcams. We note from our experiments that the images from the PTZ camera do not have significant advantages compared to the freely available Webcam images for the task at hand. For details on PTZ camera processing, see Prabha (2019).



a) Deeplab v3+ architecture b) Deep-U-Lab version

Figure 2. CNN architectures used in our lake ice monitoring system.

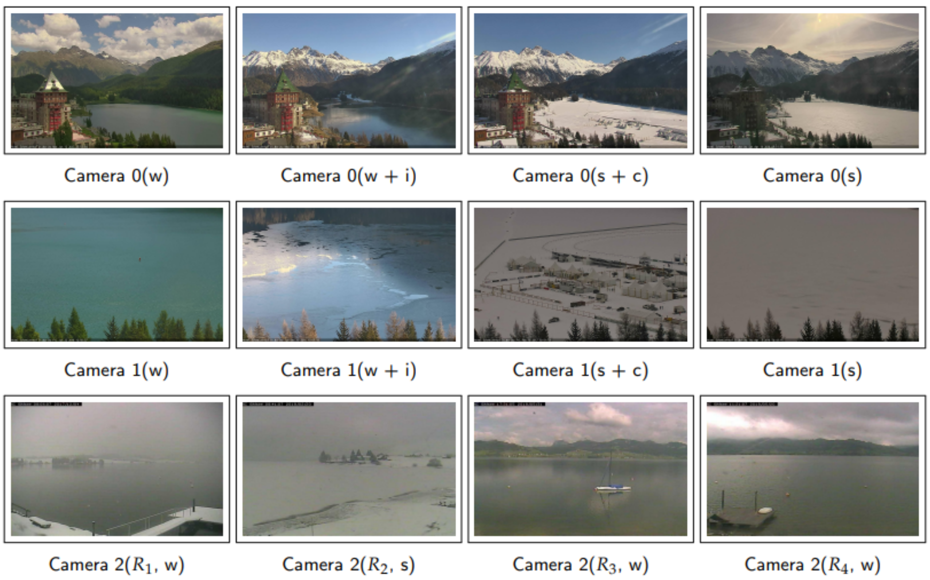


Figure 3. *Photi-LakeIce* dataset. Rows 1 and 2 display sample images from cameras 0 and 1 (St. Moritz) respectively. Row 3 shows example images of camera 2 (Sihl, non-stationary, some rotations (R1, R2, etc.) are also displayed). The state of the lake: *water(w), ice(i), snow(s), clutter(c)* is also displayed in brackets.

UAV data processing. We flew the ETHZ UAV above the lake Sils during two break-up periods and captured both RGB and thermal images of the partially frozen lake. Due to lower quality and resolution and time restrictions, the thermal images were not processed. The RGB data from the UAVs is geo-referenced (relatively) using the off-the-shelf *Pix4d mapper* software. We perform semantic segmentation of the RGB UAV images into 4 different classes (*ice, snow, water* and *clutter*). The *clutter* class represents all pixels (including background) except *ice*, *snow* and *water.* We fine-tuned a Deeplab v3+ model pre-trained on the *Photi-LakeIce* dataset with the UAV images in order to do so. We notice that, though the distributions of *ice*, *snow* and *water* classes in UAV images (RGB) are similar to that of Webcam images, the lack of domain knowledge for the class *clutter* requires an adaptation, that's one of the reasons why we fine-tuned the CNN.

3. Results

MODIS and VIIRS results. To analyse the performance of our methodology on MODIS and VIIRS satellite data, we perform four-fold cross-validation tests (see Table 1 for results) and also plot the cross-validation results of four different classifiers (including two different versions of SVM), see Figs. 4 and 5. Here, we show the mean classification accuracy (mAcc) and mIoU scores. It can be inferred from Table 1, Figs. 4 and 5 that our approach achieves excellent results including the good generalisation performance across lakes (from the same geographical region) and winters. For more detailed results (timeline plots, qualitative results etc.) on VIIRS and MODIS data and detailed explanations, see Tom et al. (2020b).

Table 1. Four-fold cross-validation results on MODIS and VIIRS data. The combined data of all the available lakes from both winters 2016-17 and 2017-18 are used in this analysis.

Sensor	Classifier	Feature Vector	mAcc (%)	mIoU (%)
MODIS	SVM Linear (SL)	All 12 bands	93.4	83.9
MODIS	Random Forest (RF)	10 bands (random)	98.9	97.2
MODIS	XGBoost (XG)	All 12 bands	99.3	98.3
MODIS	SVM RBF (SR)	All 12 bands	99.4	98.5
VIIRS	SVM Linear (SL)	All 5 bands	95.1	88.4
VIIRS	SVM RBF (SR)	All 5 bands	97.1	93.1
VIIRS	Random Forest (RF)	3 bands (random)	97.6	94.5
VIIRS	XGBoost (XG)	All 5 bands	97.7	94.5

Fig. 5 shows that among the four classifiers used the SVM linear classifier generalises better across winters on MODIS data. Hence, we analyse the MODIS time series (from 20 winters) using the SVM linear classifier. The 20 winter decreasing lake ice trend detected by our SVM algorithm is shown in Fig. 6. In the first row, we plot the Freeze-Up Start (FUS), Freeze-Up End (FUE), Break-Up Start (BUS) and Break-Up End (BUE) dates (for lake Silvaplana) in each winter (predicted by our algorithm) on the y-axis and the winters in chronological order on the x-axis. Note that none of the four important dates occurred between the beginning of September till the end of November. Hence, we did not display these dates to avoid having useless dates on the y-axis. The solid curves show our predictions and the corresponding dotted curves (with the same colour) display the linear trend fitted for the respective results. Note that late freeze-up, early break-up and decreasing freeze-duration trends can be inferred from this figure. Similarly, in the second row, we plot the increasing temperature trends recorded at the nearest meteorological station (Segl Maria).

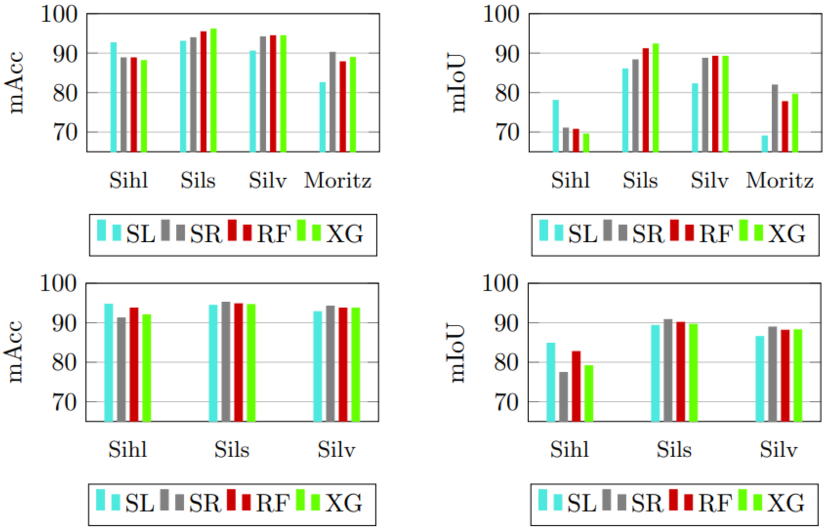


Figure 4. Generalisation across lakes results (in %) on MODIS (top row) and VIIRS (bottom row) for the classifiers SVM Linear (SL), SVM RBF (SR), Random Forest (RF) and XGBoost (XG) on lakes Sihl, Sils, Silvaplana (Silv) and St. Moritz (Moritz). For each lake, the data from two winters (2016-17, 2017-18) was combined to perform this experiment.

Figure 5. Generalisation across winters results (in %) on MODIS (top row) and VIIRS (bottom row) for the classifiers SVM Linear (SL), SVM RBF (SR), Random Forest (RF) and XGBoost (XG). For each winter, the data from all available lakes was combined to perform this experiment.

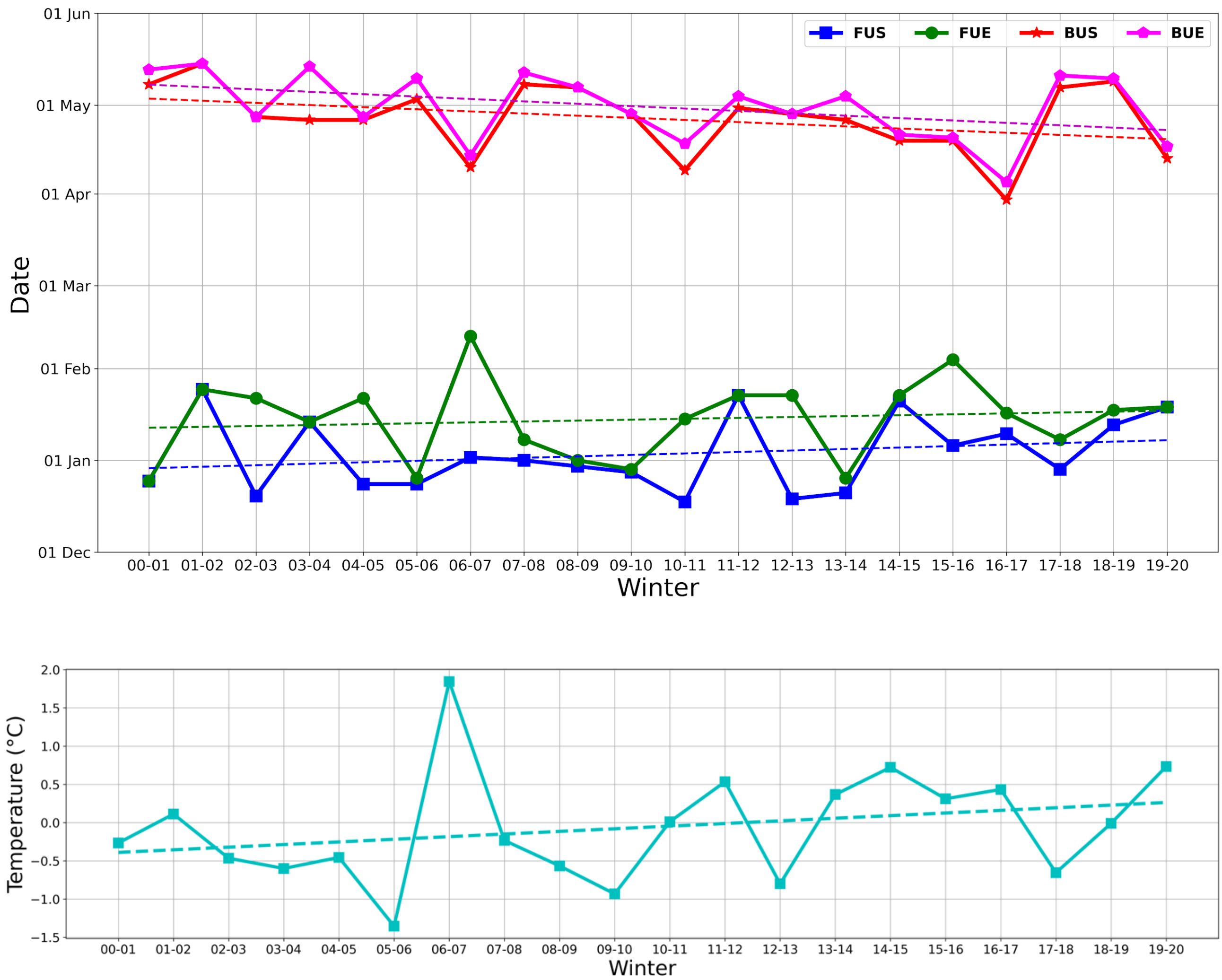


Figure 6. Row 1 shows the results from 20 year MODIS time series processing of lake Silvaplana. Our machine learning-based predictions (solid line curves) and the corresponding linearly fitted trends (dotted line curves) are shown. In each winter, dates from the beginning of December till end of May are shown on the y-axis while the winters from 2000-01 (shown as 00-01, from September 1st 2000 till May 31st 2001) till 2019-20 (19-20) are shown chronologically on the x-axis. FUS, FUE, BUS and BUE denote freeze-up start, freeze-up end, break-up start and break-up end respectively. Row 2 shows the mean temperature plot (solid cyan curve, recorded at the Segl Maria meteorological station) and the corresponding linearly fitted (increasing) trend curve (dotted cyan curve) for each winter (September 1st till May 31st) on the y-axis against the winters in chronological order on the x-axis.

Sentinel-1 and -2 results. The proposed CNN model for Sentinel-1 SAR data reaches mIoU scores of >90% on average (for all lakes), and >84% even for the most difficult lake. Additionally, we perform cross-validation tests and our algorithm generalises well across other lakes and winters. Table 2 shows the effect of the different polarisations. Note that the best results are obtained when both the polarisations are fed as input to the CNN. Sample qualitative results on SAR data are shown in Fig. 7. For detailed quantitative and qualitative results (generalisation across lakes and winters results, precision-recall curves, timeline plots etc.) and thorough discussions, see Tom et al. (2020a) and Aguilar (2020). Sample qualitative results on Sentinel-2 data using SVM is also shown in Fig. 7. For more results on Sentinel-2 data analysis, see Aguilar (2020).

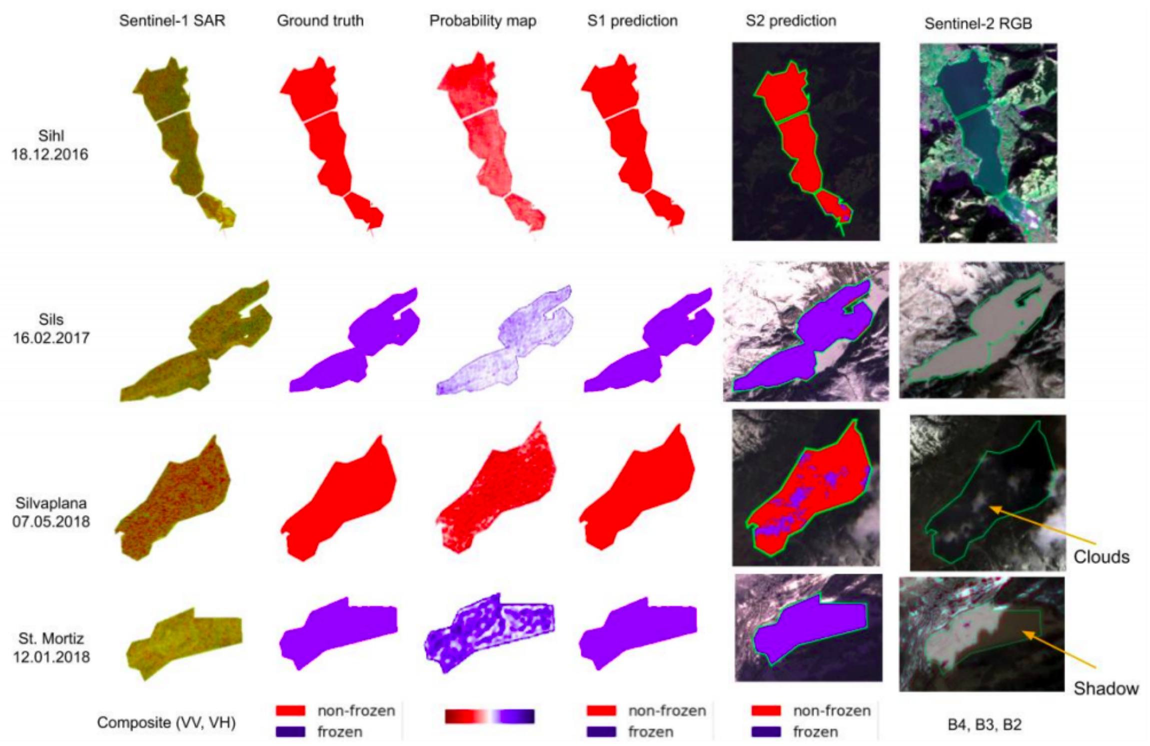


Figure 7. Sentinel-1 SAR data and Sentinel-2 analysis. Qualitative results for lake Sihl on a non-frozen day (row 1), lake Sils on a frozen day (row 2), lake Silvaplana on a non-frozen day with clouds (row 3), and lake St. Moritz (row 4) on a frozen day with shadow from clouds or nearby mountains are shown. For each lake we display the Sentinel-1 composite (RGB = VV, VH, 0) image (column 1), the ground truth (column 2), the predicted probability map from Deeplab v3+ (more red means more non-frozen and blue frozen), and the corresponding binary classification map (column 4). Additionally, column 5 shows the respective prediction from SVM, and in column 6, a pseudo RGB Sentinel-2 image (combining bands B4, B3, B2) for better visual interpretation.

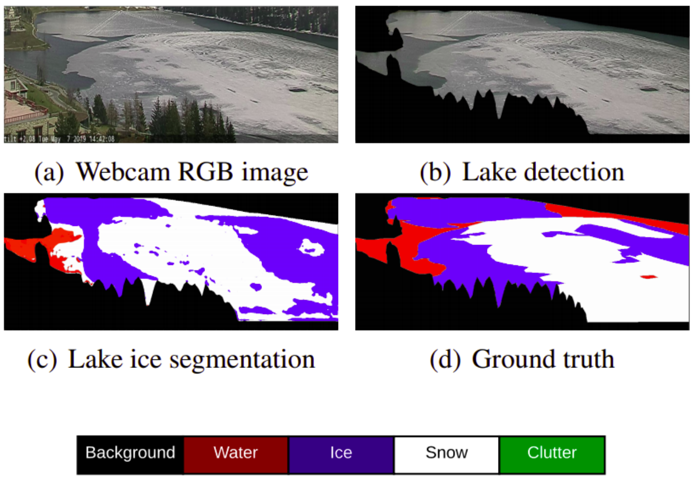
Table 2. Sentinel-1 SAR processing results. Per-class IoU values for frozen and non-frozen classes are shown to study the effect of different polarisations (VV, VH) as input. Data from all four lakes from winter 2016 − 17 is tested using a model trained on the data from all four lakes from winter 2017 − 18.

	VV, VH	**VH**	**VV**
Non-frozen	90.4%	75.2%	88.6%
Frozen	80.8%	39.7%	76.7%

Results on Webcams and crowd-sourced data. We have tested the new *Deep-U-Lab* model's ability to generalise across data from multiple camera views, lakes and two different winters. On average, it achieves IoU values of ≈71% across different cameras and ≈69% across different winters, greatly outperforming prior work (Tom et al., 2019). Going even further, our model even achieves 60% IoU on arbitrary images collected from photo-sharing web sites. Table 3 shows the quantitative results when 75% of the images from a camera is used for training and the rest 25% for testing. Note that our approach outperforms the current state-of-the-art (Tiramisu network, Tom et al., 2019). A sample qualitative result is displayed in Fig. 8. For detailed quantitative and qualitative results and discussion, see Tom et al. (2020b) and Prabha et al. (2020).

Table 3. Results (IoU) of same camera training/test experiments. We compare our results with the Tiramisu Network (Tom et al. 2019, shown in grey; results exist only for winter 16-17 and lake St. Moritz). Cameras 0 and 1 monitor lake St. Moritz and camera 2 lake Sihl.

Training set		Test set		Water	Ice	Snow	Clutter	mIoU
Camera	**Winter**	**Camera**	**Winter**					
Camera 0	16–17	Camera 0	16–17	0.98/0.70	0.95/0.87	0.95/0.89	0.97/0.63	0.96/0.77
Camera 0	17–18	Camera 0	17–18	0.97	0.88	0.96	0.87	0.93
Camera 1	16–17	Camera 1	16–17	0.99/0.90	0.96/0.92	0.95/0.94	0.79/0.62	0.92/0.85
Camera 1	17–18	Camera 1	17–18	0.93	0.84	0.92	0.84	0.89
Camera 2	16–17	Camera 2	16–17	0.79	0.62	0.81	—	0.74
Camera 2	17–18	Camera 2	17–18	0.81	0.69	0.86	—	0.79



(a) Webcam RGB image (b) Lake detection

(c) Lake ice segmentation (d) Ground truth

(e) Colour code.

Figure 8. (a) Example Webcam image of lake St. Moritz, from the *Photi-LakeIce* dataset, (b) lake detection result, (c) lake ice segmentation result, (d) corresponding ground truth labels and (e) the colour code used. The class *clutter* (green), though occasionally present in lake St. Moritz, does not occur in this example.

Results of UAV data. We tested the CNN fine-tuned on the RGB UAV images and achieved very good results. A sample qualitative result is shown in Fig. 9. On a subset of the dataset that was manually labelled (21 images), our algorithm obtained a mIoU of > 91% on all classes.

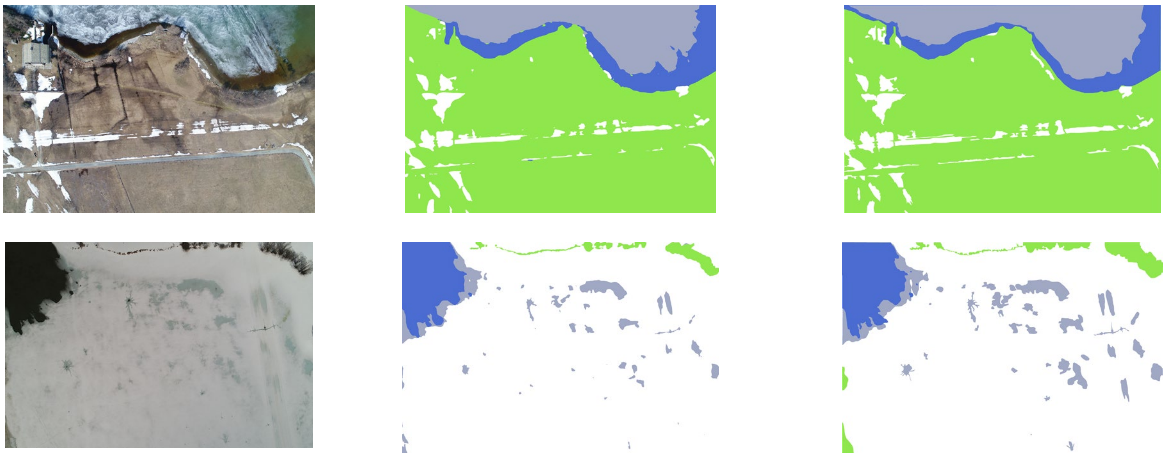


Figure 9. UAV data processing results. Colour code (blue: *water*, white: *snow*, grey: *ice*, green: *clutter*). Anything other than *ice*, *water* and *snow* is considered as *clutter* (including the background).

In this project, we estimate the *ice-on* and *ice-off* dates. Table 4 shows the results for winter 2016-17 using mainly the Webcam and combined MODIS and VIIRS results. For both, the training was using data from winter 2017-18, while testing and here presented results were from winter 2016-17. Thus, the results are worse than training and testing from winter 2016-17 (see e.g. the MODIS/VIIRS ice-on/off dates in Manu et al., 2019), but we do this on purpose to present results that should be more realistic with training from one winter and testing for multiple ones. When combining MODIS and VIIRS, we use the VIIRS results and when there are VIIRS gaps (e.g. due to clouds) we use the MODIS results. For reasons of completeness in the column MODIS+VIIRS we also present the dates from training using the winter 2016-17 (first MODIS, then VIIRS, whereby for MODIS and Silvaplana ice-on two dates were estimated).

Table 4. Ice-on/off dates (winter 2016-17). Ground truth dates are shown in the order of confidence in case of more than one candidate. See also additional explanations in text.

Dates	**Ground truth (Webcam manual interpretation)**	**MODIS + VIIRS**	**Webcams**	**In-situ (temperature-based)**
ice-on (Sihl)	1 January 2017	3 January 2017 (3.1.17, 3.1.17)	4 January 2017	28–29 December 2016
ice-off (Sihl)	14 March 2017, 15 March 2017	10 March 2017 (10.3.17, 12.3.17)	14 February 2017	16 March 2017
ice-on (Sils)	2 January 2017, 5 January 2017	6 January 2017 (6.1.17, 6.1.17)	-	31 December 2016
ice-off (Sils)	8 April 2017, 11 April 2017	31 March 2017 (12.4.17, 7.4.17)	-	10 April 2017
ice-on (Silvaplana)	12 January 2017	15 January 2017 (1.1.17/15.1.17, 11.1.17)	-	14 January 2017
ice-off (Silvaplana)	11 April 2017	30 March 2017 (8.4.17, 8.4.17)	-	14 April 2017
ice-on (St. Moritz)	15–17 December 2016	1 January 2017 (18.12.16, no data)	14 December 2016 (15.12.16/16.12.16)	17 December 2016
ice-off (St. Moritz)	30 March–6 April 2017 (data missing)	7 April 2017 (9.4.17, no data)	18 March–26 April 2017 (data missing)	5–8 April 2017

In table 4, the ground truth and in-situ (temperature-based) data were estimated in a very similar project just before the current one (Tom et al., 2019). The satellite results are influenced by the cloud problem, while with Webcams (influencing also the ground truth), due to technical problems, no data were acquired during some time periods. The above explain to a certain extent the time difference (sometimes significant) among the methods regarding the ice-on/off dates. Note, that the GCOS accuracy requirement for the estimation of ice-on/off dates is +/- 2 days.

Table 5 displays the intercomparison of the parameters of the various input data used in our analysis. Intercomparison of the pros and cons of our methodologies are shown in Table 6.

Table 5. Intercomparison of parameters of used data (for lake monitoring).

Parameter	**MODIS**	**VIIRS**	**Sentinel-2**	**Sentinel-1 SAR**	**Webcams**	**Crowd-sourced**	**UAV**
Temporal resolution	1 day	1 day	5 days	1.5-3 days	≈ min – 1 hour	random	Variable, up to ms
Spatial resolution	250-1000 m	375-750 m	10-60m	10m	ca. 4 mm to 4 m	Random, generally in m-km range	4 cm (for given data acquisition)
Spectral resolution	36 bands (0.41-14.24 μm)	22 bands (0.41-12.01 μm)	13 bands (0.44-2.2 μm)	C-band, 4 polarisations (mainly VV, VH)	RGB	RGB	mainly RGB
Availability	very good (via VIIRS continuity)	very good	very good	very good (HV/ HH only partially available)	Increasing, weakly controlled, mainly in touristy areas	Huge, uncontrolled, mainly in touristy areas	Increasing, increasing flight restrictions
Costs	free	free	free	free	free	free	UAV, costs per flight
Cloud mask issues	slight	slight	slight	NA	NA	NA	NA
Cloud issues	severe	severe	severe	practically nil	negligible	negligible	negligible

Table 6. Intercomparison of the processing methods versus input sensor images.

Parameter	MODIS, VIIRS, Sentinel-2	Webcams, Crowd-sourced images	Sentinel-1 SAR	UAV images
Automation	High	High	High	High
Training complexity	Very little	Medium (transfer learning greatly reduces training)	Medium (transfer learning greatly reduces training)	Medium (transfer learning greatly reduces training)
Pixel-wise training labels	Not necessary (fully- or non-frozen days used)	Necessary	Not necessary (fully- or non-frozen days used)	Necessary
Pre-training on large datasets	Not needed	Needed	Needed	Needed
Processing load (common PCs)	Very low (in the order of a few minutes)	high, needs Graphic Processing Units (GPUs)	high, needs GPUs	high, needs GPUs
Near-real time response	Yes	Possible (excluding training)	Possible (excluding training)	Possible (excluding training)

4. Outreach

A webpage (https://prs.igp.ethz.ch/research/current_projects/integrated-lake-ice-monitoring-and-generation-of-sustainable--re.html) presents important project information (description, publications, free code/data links etc.).

The following papers / posters were presented in scientific events:

Tom M., Rothermel M., Baltsavias E., Schindler K., 2019. Semantic Segmentation of Ice in selected Swiss Lakes. 1st Swiss Workshop on Machine Learning for Environmental and Geosciences (MLEG), Dübendorf, Switzerland, January. Abstract available at: https://www.mleg.ethz.ch/wp-content/uploads/2019/01/MLEG_abstracts.pdf (accessed on 26 October 2020).

Prabha R., Tom M., Rothermel M., Baltsavias E., Leal-Taixe L., Schindler K., 2020. Lake Ice Monitoring with Webcams and Crowd-Sourced Images. Presentations of ISPRS 24th Congress (virtual), September, (accessed on 26 October 2020).

Tom M., Aguilar R., Imhof P., Leinss S., Baltsavias E., Schindler K., 2020. Lake Ice Detection from Sentinel-1 SAR with Deep Learning. Presentations of ISPRS 24th Congress (virtual), September (accessed on 26 October 2020).

Publications during the project duration (see references below) include Tom (2020), Prabha et al. (2020) and Tom et al. (2020a, 2020b). A journal paper on MODIS/VIIRS time series analysis will be submitted shortly.

5. Publication of data and software

- Photi-LakeIce benchmark dataset (Webcam images) is available at: https://github.com/czarmanu/photi-lakeice-dataset
- Code of our Deep-U-Lab approach (for processing of Webcams and crowd-sourced images) is available at: https://github.com/czarmanu/deeplab-lakeice-webcams
  Link to download the Deep-U-Lab model pre-trained on the *Photi-LakeIce* dataset: https://share.phys.ethz.ch/~pf/tommdata/Pre-trained_Model.tar.xz
- Code of our Sentinel-1 SAR-based approach is available at: https://github.com/czarmanu/sentinel_lakeice

Link to download the Deeplab v3+ model pre-trained on our SAR dataset: https://share.phys.ethz.ch/~pf/tommdata/Sentinel-1_SAR/pre-trained-model.zip

6. Conclusions

From our experiments and results, we conclude that the state-of-the-art machine (and especially deep) learning algorithms are very effective for lake ice observation using various sensors such as optical satellite data (VIIRS, MODIS and Sentinel-2), radar satellite data (Sentinel-1 SAR) and Webcam data. For SVM, best results were acquired by using the linear kernel and all the useful MODIS and VIIRS channels, while multi-temporal analysis did not bring any remarkable improvement. Each sensor data and methodology has its pros and cons. Data from optical satellites faces problems due to clouds which is a bottleneck. This problem is practically avoided with Sentinel-1 SAR. Webcam images are particularly useful for monitoring small lakes and reducing the cloud problem. The availability of long time series of MODIS (since 2000) is useful to learn the decreasing Swiss lake ice trends.

In this project, we showed that machine (and especially deep) learning, even if little explored for this application, is a powerful and robust tool for largely automated lake ice estimation.

7. Outlook

Improvements should be pursued for generalisation among different winters, lakes and Webcams, and these should be validated by new test data. The acquisition of reference data is time consuming and based on visual interpretation of images. To reduce this, one possibility is to estimate lake ice by multiple methods (if possible, more than two), and then compare the results, to increase their reliability. However, this may not be feasible on a daily basis. Sanity checks can include temperature from meteorological stations close to the lakes. SAR processing could be possibly extended by using polarimetric and interferometric information. Another possible future direction could be multi-sensor fusion approaches for lake ice monitoring using machine (deep) learning by mapping the input data to a new feature space independently of the type of the sensor data.

An operational lake ice estimation should be based on optical satellite images, augmented by SAR ones. For small lakes and coarse spatial resolution optical satellite images, Webcams should be used.

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