Hive Wireless Sensor Network

Release alpha

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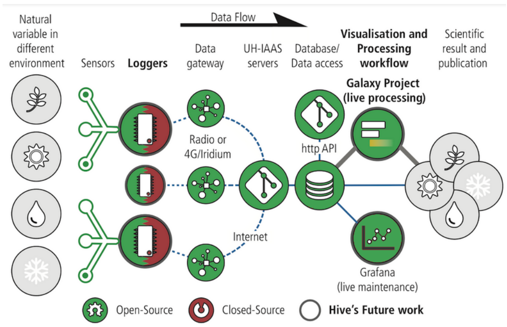
CHAPTER ONE

INTRODUCTION

Welcome to the documentation of the Hive Wireless Sensor Network (Hive WSN) system developed at Department of Geosciences of the University of Oslo. The Hive WSN consists of a system to collect data in remote and cold regions using the technology available thanks to the Internet of Things (IoT) industry. This system is build to the maximum extent on open-source technology .

This documentation intends to provide as much information as possible on the functionning of the entire system for transparency towards the end user of the data. You will find a section describing the hardware



1.1 Deployed Network

We currently have two test sites, one in mainland Norway, and another one in Ny-Ålesund, Svalbard. Data from the network in Svalbard will be available freely through the SIOS portal.

1.1.1 Finse, Norway

The network in Finse is primarily a test ground for the equipment before being send elsewhere. The network is spread around the research station of Finse.. Data are available upon request.

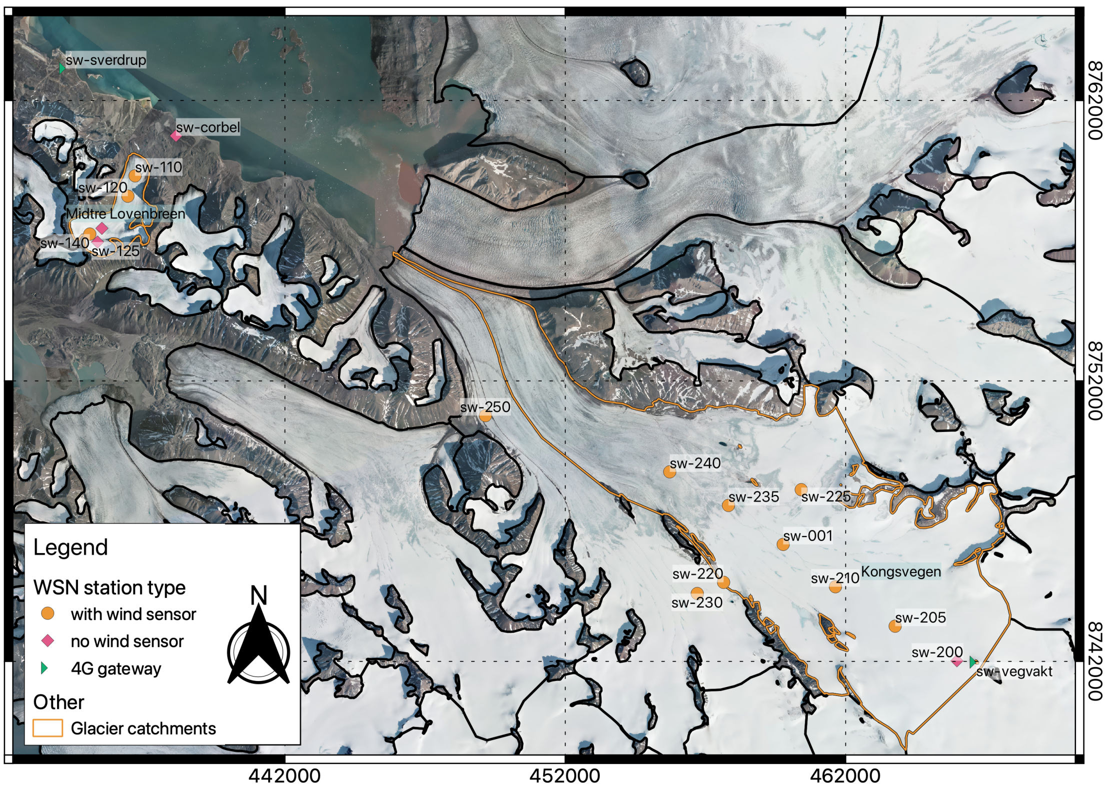
Due to the very harsh weather, the network is currently partly functionning.

1.1.2 Norwegian Permafrost Borehole

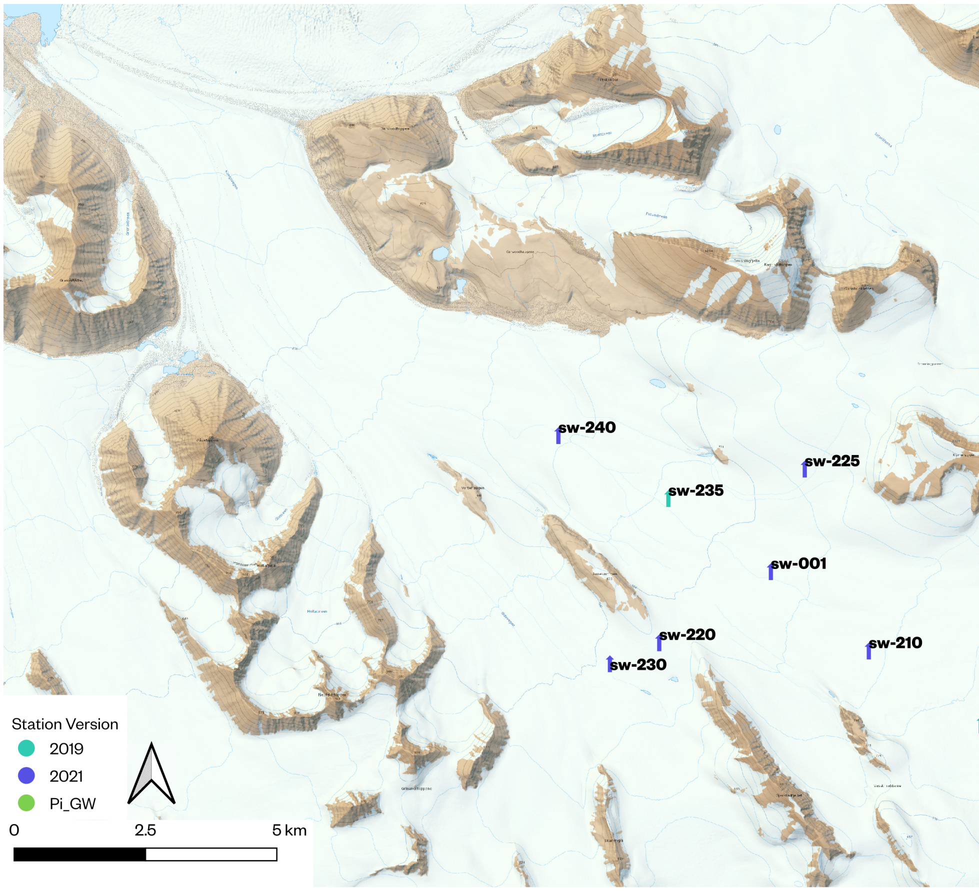
Hive WSN stations equip 4 permafrost borehole spread across the norwegian mountains to record ground temperatures.

1.1.3 Ny-Ålesund, Svalbard Archipelago

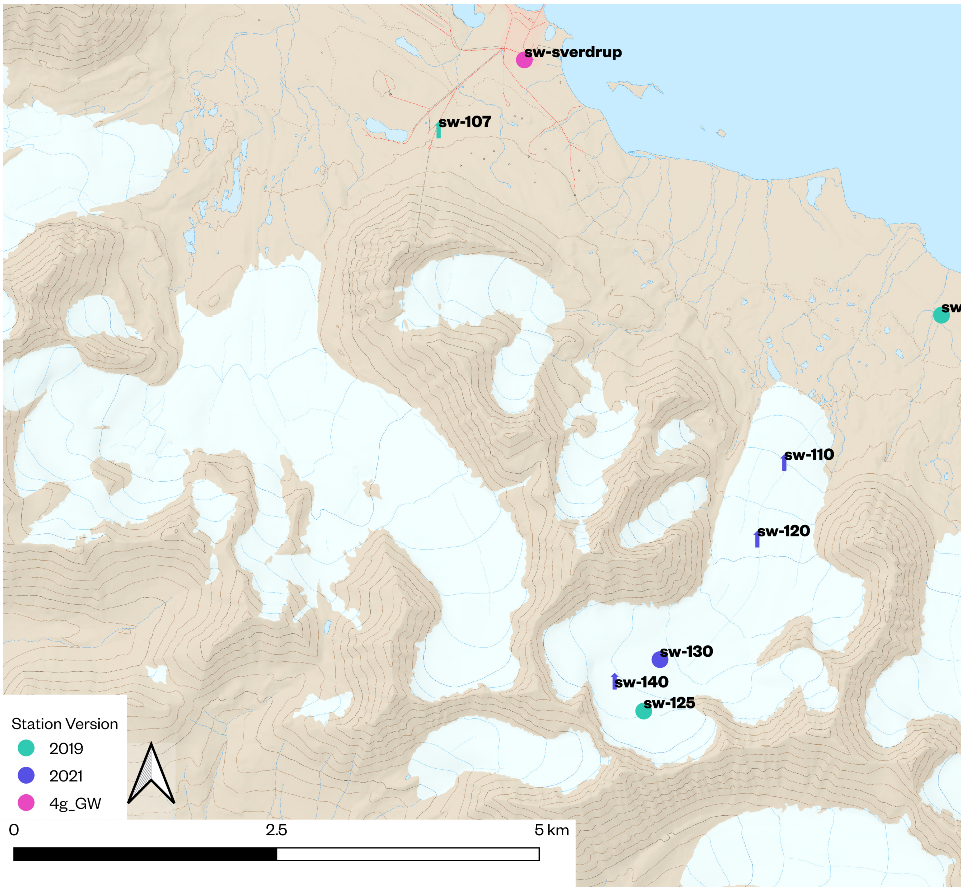
Our largest network is deployed aroud the region of Ny-Ålesund in Svalbard. It is currently spread over two glaciers Kongsvegen, and Midtre-Løvenbreen (aka. two sub networks). The networks are pushing data to the servers



General view

Kongsvegen glacier sub network as of 2021: 

Midtre Løven glacier sub-netwrok as of 2021:



1.2 Financial Support

This development is supported by the eInfrastructure hub UiO Hive, and implemented to collect data on the archipelago of Svalbard in collaboration with the Norwegian Polar Institute. Additional support from SIOS.

CHAPTER TWO

HARDWARE DESCRIPTION

The HiveWSN kit consists of

1. a *brain* box containing the powser system, the microcontroller, the communication system and the connectivity to the sensors.
2. a set of sensors either commercially available or custom built at the Department of Geosciences at UiO as part of the UiO Hive project.

[include a photo]

The kit is autonomous and packaged as a beam that can be installed on simple mast. The suite of sensors if customizable and depends on the puporse of the project. The main limitations in including new sensors are the communication protocol in between the microcontroller and the sensor, and the power management.

Currently, there are two versions of the WSN system: v1 from 2019, and v2 from 2021. Both are based on the board Wasmpote v15 which handle power, communication, and data brokerage. The firmware running all instances has been written as part of the project UiO Hive, and include a set of tools described in the software section.

2.1 Version 1, 2019

Version 1 is the first formalized version of the Hive system. It includes a range of solution in terms of sensors, communication protocol, and embedded resilience system.

[include photo]

2.2 Version 2, 2021

Version 2 is an upgraded version which includes a number of improvements like new sensors, larger solar panel and enclosure, an added microcontroller to control sensors only. This version was made compatible with the Lora radio network solution, with its own libraries to perform tree topology with Lora radios.

[include photo]

2.3 Sensors

The sensors used on the stations are the following:

Sensor name	Sensor type	Version	Datasheet
VL53L1	Lidar	v1, v2	Datasheet
MLX90614 IR	Thermal IR	v1, v2	Datasheet
VEML7700	Ambient light	v2	Datasheet
AS7341	Spectrometer	v2	Datasheet
VCNL-4040	Proximity NIR sensor	v2	Datasheet
BME280	Temperature, humidity, pressure	v1, v2	Datasheet
TMP117	Temperature	v2	Datasheet
TMP102	Temperature	v1	Datasheet
SHT31	Temperature, humidity	v2	Datasheet
ATMOS 22	Wind, temperature	v1, v2	Datasheet
CTD 10	Water temperature, pressure, conductivity	v1, v2	Datasheet
DS18B20	Temperature	v1, v2	Datasheet
MB7389	Temperature	v1, v2	Datasheet

All sensors use digital comminucation protocols such as I2C, SDI-12, or One-Wire.

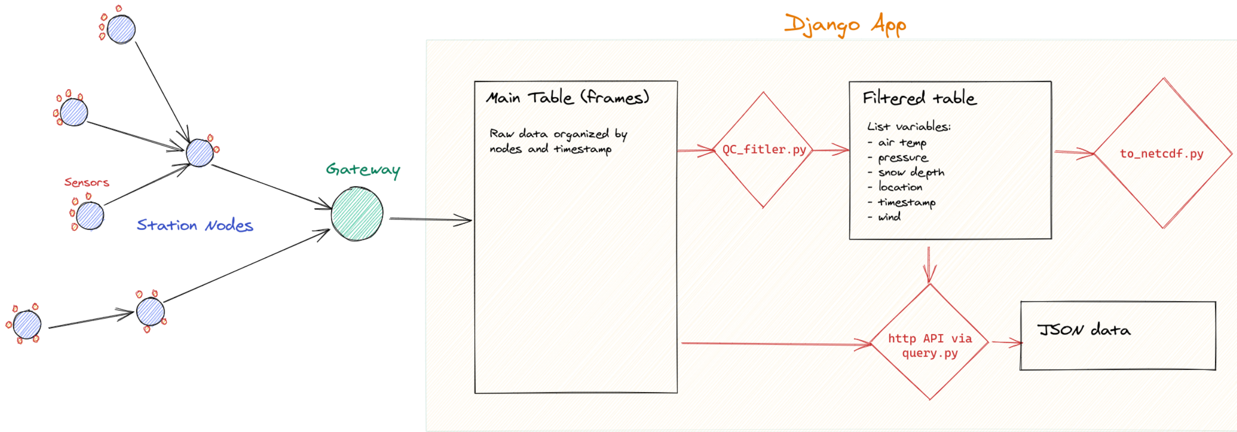
Sampling can be set to any time intervals, though in most cases all sensors are sampled every 10 minutes as a trade of for temporal granularity and power saving. All data is associated to its ampling time.

CHAPTER

THREE

DATABASE SYSTEM DESCRIPTION

The General concept of the data pipeline consists of the sensors sampling at regular intervals predefined in each nodes. Data are stored locally and also put in a queue to be sent out via radio, 4G or Iridium. Data are then stored in a PostgreSQL database in raw format. This table is accessible by *http* queries using the API `wsn_client` (restricted access). Those data have no quality control and are stored as is. Currently under construction, data are then filtered, flagged for quality, and aggregated into a table. Those data are accessible in `JSON` format via *http* request (restricted access), or in the the case of the Svalbard network in `netcdf4` format via the SIOS dataportal.



3.1 Download Data from SIOS Dataportal

[TBA]

3.2 Download Data Directly from the UiO Django App

3.2.1 Through Grafana

Data can be downloaded interactively via the Grafana interface. The Grafana portal requires login information.

1. go to the desired dashboard
2. define the time range
3. click on the panel title > `more ...` > `export CSV`
4. open your Download folder, here it is

3.2.2 Through `http` request

The Django database can be queried via `http` request, and return data organized in a json object. [write about the http request structure/fields]

Python query function

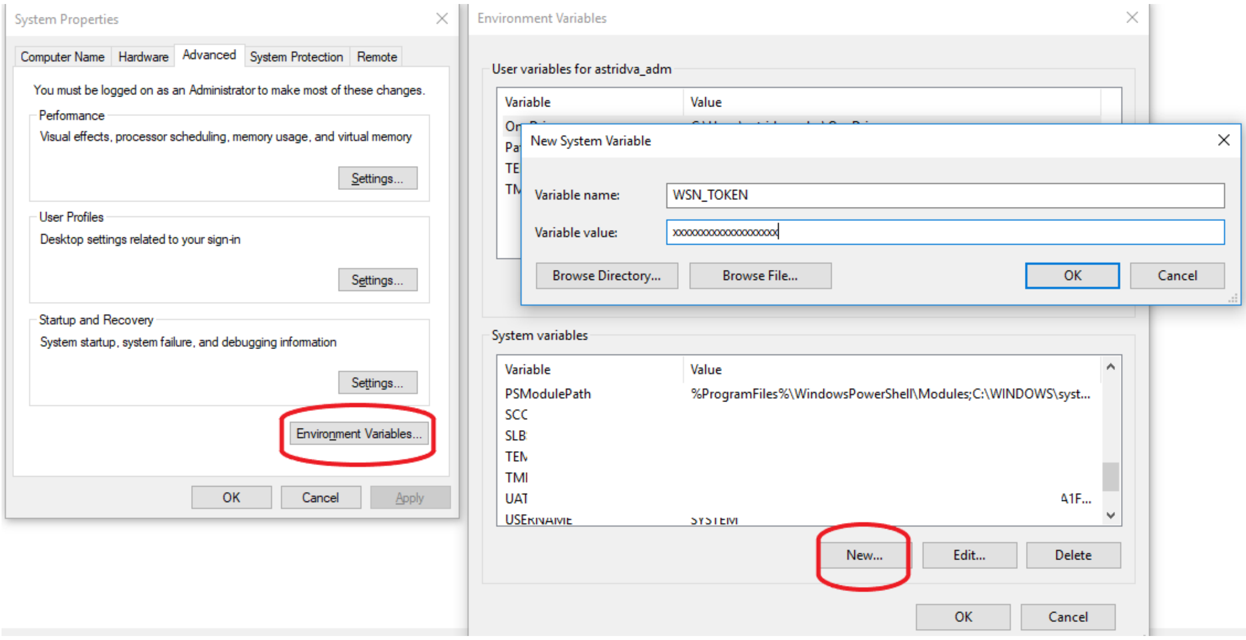
You will need a Python 3.7 environment with the libraries requests, and pandas installed.

Assuming you have Anaconda 3 installed on your machine, type the following in your terminal to create a suitable environment:

```
conda create --name uioData  python=3.8
conda activate uioData
conda install pandas requests ipython

# in case you use Jupyter Lab
conda install ipykernel
ipython kernel install --user --name=uioData

# other python package of interest for data processing
conda install numpy matplotlib scikit-learn

# cd to a good location to clone the WSN_CLIENT repository
git clone git@github.com:spectraphilic/wsn_client.git  #uses SSH key to query github␣
↪otherwise use https: git clone https://github.com/spectraphilic/wsn_client.git

pip install -e [pathTo]/wsn_client     # point the pip install to where you cloned the␣
↪wsn_client package
```

From there you will need to obtain a token from the database *administrators*, granting you access to the database via http. You need to add the TOKEN as an environment variable. On Unix system (Linux and MacOS) add to `.bashrc` file the line `export WSN_TOKEN='xxxxx'`. Replace the `'xxxxx'` by the actual token. Then you should be able to access the TOKEN in a python console (after restarting you terminal) with the following Python command: `TOKEN = os.getenv('WSN_TOKEN')`

For Windows, you need to add the WSN_TOKEN to your environment variables. One way to do this is to right click `PC -> Properties -> Advanced System settings -> Environment Variables`



Brief example to download data

```
from wsn_client import query
import datetime, os

start = datetime.datetime(2019, 6, 1)
end = datetime.datetime(2019, 6, 15)

df_kong = query.query('postgresql', name='sw-002', time__gte=start, time__lte=end, limit=2000000000000)
df_kong.head()
```

Selecting data (rows)

First choose the database to pull data from, choices are clickhouse (for raw data from finse/mobile flux), and postgresql (for everything else). How data is selected depends on the database used. ClickHouse: `query('clickhouse', table='finseflux_Biomet', ...)`. Choices for table are: finseflux_Biomet, finseflux_StationStatus, mobileflux_Biomet and mobileflux_StationStatus. PostgreSQL:

```
query('postgresql', name='eddypro_Finseflux', ...)
query('postgresql', serial=0x1F566F057C105487, ...)
query('postgresql', source_addr_long=0x0013A2004105D4B6, ...)
```

Data from PostgreSQL can be queried by any metadata information, most often the name is all you need.

Selecting fields (columns)

If the fields parameter is not given, all the fields will be returned. This is only recommended to explore the available columns, because it may be too slow and add a lot of work on the servers. So it is recommended to ask only for the fields you need, it will be much faster. Examples:

```
query('clickhouse', table='finseflux_Biomet', fields=['LWIN_6_14_1_1_1', 'LWOUT_6_15_1_1_
↪1'], ...)
query('postgresql', name='eddypro_Finseflux', fields=['co2_flux'], ...)
```

The field 'time' is always included, do not specify it. It's a Unix timestamp (seconds since the Unix epoch). The rows returned are ordered by this field.

Selecting a time range

Use the parameters time__gte and/or time__lte to define the time range of interest. The smaller the faster the query will run. These parameters expect a datetime object. If the timezone is not specified it will be interpreted as local time, but it's probably better to explicitely use UTC. Example:

```
query(
    'clickhouse', table='finseflux_Biomet',
    fields=['LWIN_6_14_1_1_1', 'LWOUT_6_15_1_1_1'],
    time__gte=datetime.datetime(2018, 3, 1, tzinfo=datetime.timezone.utc),
    time__lte=datetime.datetime(2018, 4, 1, tzinfo=datetime.timezone.utc),
    ...
)
```

Limiting the number of rows

The limit parameter defines the maximum number of rows to return. If not given all selected rows will be returned. Example:

```
query(
    'clickhouse', table='finseflux_Biomet',
    fields=['LWIN_6_14_1_1_1', 'LWOUT_6_15_1_1_1'],
    time__gte=datetime.datetime(2018, 3, 1, tzinfo=datetime.timezone.utc),
    time__lte=datetime.datetime(2018, 4, 1, tzinfo=datetime.timezone.utc),
    limit=1000000,
)
```

Aggregates

Instead of returning every data point, it's possible split the time range in intervals and return an aggregate of every field over an interval. This can greatly reduce the amount of data returned, speeding up the query. For this purpose pass the interval parameter, which defines the interval size in seconds. The interval is left-closed and right-open. The time column returned is at the beginning of the interval. By default the aggregate function used is the average, pass the interval_agg to specify a differente function. Example (interval size is 5 minutes):

```
query(
    'clickhouse', table='finseflux_Biomet',
    fields=['LWIN_6_14_1_1_1', 'LWOUT_6_15_1_1_1'],
    time__gte=datetime.datetime(2018, 3, 1, tzinfo=datetime.timezone.utc),
    time__lte=datetime.datetime(2018, 4, 1, tzinfo=datetime.timezone.utc),
    limit=1000000,
    interval=60*5,
    interval_agg='min',
)
```

If using postgresql the available functions are: avg, count, max, min, stddev, sum and variance. If using clickhouse any aggregate function supported by ClickHouse can be used, see the clickhouse documentation page. Using aggregates requires the fields paramater as well, it doesn't work when asking for all the fields.

Intervaled data, but not aggregates

For certain use cases, it might be useful to get instant measurements for chosen interval, but not averaged or similarly aggregated. An example could be to get every a temperature measurment every five minutes - but the *instant* measurement, not an averaged number over that half hour.

The method depends on using clickhouse or postgresql.

For clickhouse, use the `interval_agg=None` argument. NB: **no** string qoutes around `None`, opposite to the how the other arguments should be stated. When using `=None`, the query will return the first dataframe of that interval, where there is data.

A slightly different result is given if one uses the `interval_agg='any'`. In this case, the frames contains the measurement data from the same frames as when using `=None`, but the *timestamp* will not be the original timestamp of the instant measurement, but (as with all interval_agg arguments), the left bound timestamp.

In the case of no missing dataframes and when querying for instance for every 5 minut instants data, the results of using `=None` and `='any'` are the same, and will have timestamps on every whole 5 minutes. If some dataframes are missing, however, `=None` gives the original timestamp matching the data, whereas `='any'` will give the rounded timestamp.

For postgresql, simply leave out the `interval_agg` of the query alltogether, while keeping `interval`.

Tags (PostgreSQL only)

With PostgreSQL only, you can pass the tags parameter to add metadata information to every row. Example:

```
query(
    'postgresql', name='fw-001',
    fields=['latitude', 'longitude'],
    tags=['serial'],
)
```

In this example, the data from fw-001 may actually come from different devices, maybe the device was replaced at some point. Using the tags parameter we can add a column with the serial number of the devices. Tags don't work with aggregated values.

Returns

This function returns by default a Pandas dataframe. Use `format='json'` to return instead a Python dictionary, with the data as was sent by the server, in a json format.

Debugging

With debug=True this function will print some information, useful for testing. Default is False.

Note on timestamps

The data are stored with timestamp in UTC timezone. If the timezone is not indicated in the Datetime object of the query, by default the timestamp will be interpretated with your computer's local timezone. It is therefore important to indicate the timezone in which you would like the timestamp to be referenced in. Therefore it is good practice to use UTC datetime object using the following syntax: `datetime.datetime(2018, 7, 1,tzinfo=datetime.timezone.utc)`.

Example script to download data via the Python 3.7 function

```
from wsn_client import query
import datetime, os

start = datetime.datetime(2018, 2, 1)
end = datetime.datetime(2018, 2, 15)
#start = end - datetime.timedelta(days=150)

# Get data from CR6 station on Austfonna
serial_perm = 2264
'''
example of available variables
{'DT': 2.05, 'TCDT': 2.039, 'WS_ms': 5.862, 'RH_Avg': 100, 'RH_Max': 100, 'BP_mbar': 972, 'WindDir
↪': 197, 'AirTC_Avg': -2.63, 'AirTC_Max': -2.494, 'AirTC_Min': -2.938, 'CG3Dn_Avg': -4.194,
↪'CG3Up_Avg': -11.78, 'CM3Dn_Avg': 164.3, 'CM3Up_Avg': 196.9, 'WS_ms_S_WVT': 6.188, 'BP_mbar_
↪test': 1029, 'WindDir_D1_WVT': 202.2, 'Batt_CR1000_Min': 14.76, 'PTemp_CR1000_Avg': 2.472}
'''
var_oi_perm = ['AirTC_Avg','RH_Avg']
df_perm = query.query('postgresql',fields=var_oi_perm, serial=serial_perm,
                      time__gte=start, time__lte=end, limit=2000000000000)
df_perm.head()
```

3.2.3 Matlab Query Example

This example query the database via the http API. The http request has the same structure as for Python. Here is an example code to build it in Matlab and query the database via TOKEN authentification. The code returns the data into a Matlab table.

```
% read Austfonna AWS data from database...
% TVS, March 2020
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

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```
clear
close all

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% USER INPUT, edit here
% desired period
dt_begin = datenum(2020,1,1);
dt_end = datenum(2020,2,15);

% desired variables...
% there are possibilities for specifying individual variables, but if not
% specified, we read all.
% available vars:
% 'Ah_hi': 0, 'BattV': 0, 'LoadV': 0, 'V_Ref': 0, 'Ah_low': 0, 'Batt_I': 0, 'DS2_TC': 'NAN', 'DS2_WS
↪': 'NAN', 'Load_I': 0, 'DS2_DIR': 'NAN', 'Hour_hi': 0, 'DS2_Gust': 'NAN', 'Hour_low': 0, 'Ah_tot_hi
↪': 0, 'Ah_tot_low': 0, 'BattV_slow': 0, 'CNR1TC_Avg': 121072.6, 'DS2_U_mean': 'NAN', 'DS2_V_
↪mean': 'NAN', 'dgpsStatus': 1, 'RegulatorTC': 0, 'Batt_CR6_Min': 13.05, 'SolarAzimuth': 201.4,
↪ 'SunElevation': 8.26, 'PTemp_CR6_Avg': -19.89, 'modemStatus_Avg': 1}
% 'DT': 2.05, 'TCDT': 2.039, 'WS_ms': 5.862, 'RH_Avg': 100, 'RH_Max': 100, 'BP_mbar': 972,
↪'WindDir': 197, 'AirTC_Avg': -2.63, 'AirTC_Max': -2.494, 'AirTC_Min': -2.938, 'CG3Dn_Avg': -4.
↪194, 'CG3Up_Avg': -11.78, 'CM3Dn_Avg': 164.3, 'CM3Up_Avg': 196.9, 'WS_ms_S_WVT': 6.188, 'BP_
↪mbar_test': 1029, 'WindDir_D1_WVT': 202.2, 'Batt_CR1000_Min': 14.76, 'PTemp_CR1000_Avg': 2.
↪472

vars = ["AirTC_Avg","RH_Avg"]; % ATTENTION!! must be string array (use "" instead of '')
% vars = [];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% authentication
headerFields = {'Authorization', ['Token ', 'xxxxxxxxxx']};   % replace xxxxx by TOKEN
opt = weboptions('HeaderFields', headerFields);

% dt_off for UNIX timestamp
dt_off = datenum(1970,1,1);
secondsperday = 24*60*60;

% construct the HTTP request (specific for Austfonna (serial = int(2264))
if isempty(vars)
    url = ['https://wsn.latice.eu/api/query/postgresql/',...
    '?limit=2000000000000',...
    '&serial%3Aint=2264',...
    '&time__gte=',num2str((dt_begin-dt_off)*secondsperday),...
    '&time__lte=',num2str((dt_end-dt_off)*secondsperday)];
else
    for i=1:length(vars)
        vs(i)=string(['&fields=',char(vars(i))]);
    end

    url = ['https://wsn.latice.eu/api/query/postgresql/',...
    '?limit=2000000000000',...
```

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```
    '&serial%3Aint=2264',...
    '&time__gte=',num2str((dt_begin-dt_off)*86400),...
    '&time__lte=',num2str((dt_end-dt_off)*86400),...
    char(join(vs,''))];
end

tmp = webread(url,opt);
% convert to a matlab table
data = table;
for i=1:size(tmp.rows,2)
    data(:,i)=table(tmp.rows(:,i));
    data.Properties.VariableNames{i}=tmp.columns{i};
end
% add matlab date
data.matlabdate = data.time/secondsperday+dt_off;
```

CHAPTER

FOUR

DATA ACCESS AND PROCESSING

CHAPTER

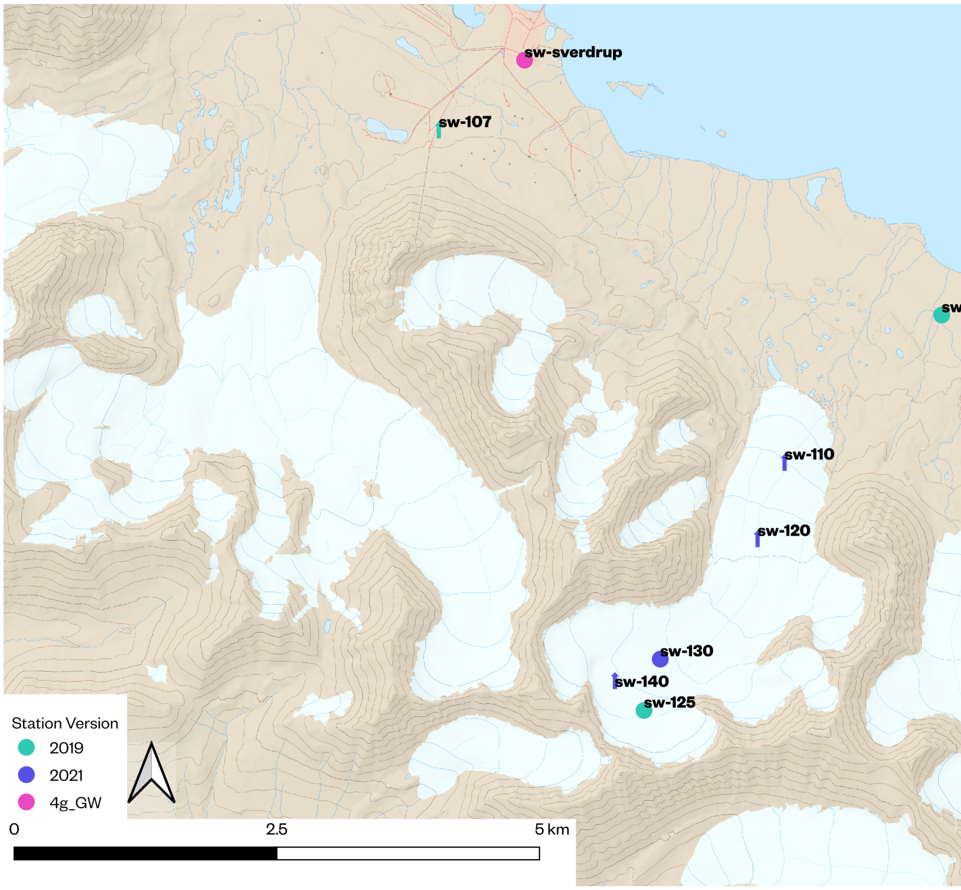
FIVE

SVALBARD NETWORK

Since 2019, two netorks have been installed in the area of Ny-Ålesund. A first one on Kongsvegen, and a second one on Midtre-Løvenbreen. Both network have different data exit system. 1) Kongsvegen data are sent via a 4G relay located on the Telenor tower at Vegvaktaren. 2) Midtre-Løvenbreen data are sent to a gateway connected to internet in Ny-Ålesund at the Sverdrup station. source/images/fig_map_WSN_new_alesunds.png

5.1 Stations Available

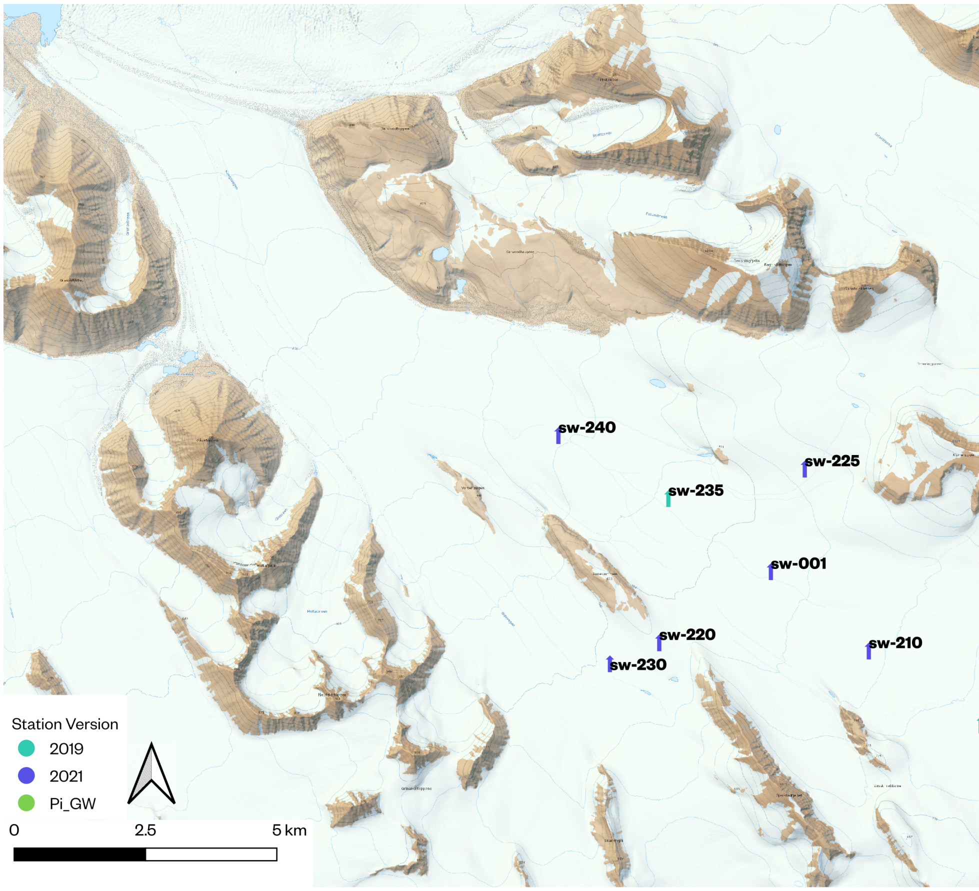
5.1.1 Midtre Løvenbreen



Midtre Løven glacier sub-netwrok as of 2021:

(Table of stations, with version, loc, db_name, glacier_name, etc)

5.1.2 Kongsvegen



Kongsvegen glacier sub network as of 2021:

(Table of stations, with version, loc, db_name, glacier_name, etc)

CHAPTER SIX

INDICES AND TABLES

- genindex
- modindex
- search