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# **SAR Surface Water Mapping**

***Release 1.1***

**National Hydrological Service**

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## **OVERVIEW OF THE PROJECT**

### **1.1 Introduction**

The National Hydrologic Services (NHS) of Canada is responsible for the upkeep and distribution of data from over 2200 gauging stations strategically placed across the country to monitor Canadian water resources. While the data these stations collect is important to the regions they are located in, the majority of water bodies and systems in this country are completely unmonitored. Many of these water bodies, especially within the prairie regions, exhibit dramatic shifts in waterbody volume and extent throughout the year, which can have significant impacts on the surrounding region. Thus, the included algorithm was developed to monitor these dynamic waterbodies using SAR, specifically data from the RADARSAT Constellation Mission (RCM).

RCM is a trio of radar satellites launched in June of 2019, that began collecting data in early 2020. SAR was chosen for an operational monitoring program such as this due to its ability to image at any time of day and through cloud cover, versus optical sensors that require sunlight and direct sight of the surface. Unlike Canada's previous generations of radar satellite (RADARSAT-1 launched in 1995, and RADARSAT-2 launched in 2007), having three satellites in a constellation allows for access to nearly the entire country each day. This large accessibility allows NHS to monitor highly volatile waterbodies, such as those in the prairies, on a biweekly basis with high spatial resolution products (5m). In addition to RCM, support for ESA's Sentinel-1 SAR missions has been implemented, increasing the flexibility and availability of SAR data products used for surface water mapping.

The waterbodies themselves are detected using open-source Random Forest machine learning which, because of its robustness, is able to accommodate a variety of SAR sensors and beam-modes. The algorithm is trained on the Global Surface Water (GSW) Dataset (<https://global-surface-water.appspot.com>), which gives each 30x30m pixel on Earth a occurrence value between 0 and 100. These values were derived from 30 years of Landsat data, and give a percentage of how often the pixel was water in the record. Scenes are trained on themselves using pixels within the scene determined from GSW to have a greater than 90% probability of being water. Results are then filtered to remove false-positives, and presented in both raster and vector formats. Additional details on the methods of the algorithm are presented by Millard et al. 2020.

The following documentation presents instructions to setup the algorithm, and an accumulation of code comments for reference and troubleshooting. An overview of the science behind the algorithm is presented by Millard et. al. 2020.

### **1.2 Reference**

Koreen Millard, Nicholas Brown, Douglas Stiff & Alain Pietroniro (2020): Automated surface water detection from space: a Canada-wide, open-source, automated, near-real time solution, Canadian Water Resources Journal / Revue canadienne des ressources hydriques, DOI: 10.1080/07011784.2020.1816499

## COMMON SETUP AND OPERATION

### 2.1 Python

The following libraries in at-least Python 3.10 are needed to run the program:

- NumPy
- SciPy
- Pandas
- Geopandas
- GDAL
- RasterStats
- Rasterio
- SciKit-Learn
- SciKit-Image
- Requests

### 2.2 Environment & config

Included with the code is a config file where the user provides the necessary settings required by SSWM in order to run. The config is split into two sections, each with their own focus as follows:

The Directories section is for input of the various directories needed by the program. Each of these should be created as a new folder within the working directory of SSWM.

The Params section is for additional information required by the program to run. Mainly, the user is able to select which type of DEM to use during preprocessing; Shuttle Radar Topography Mission (SRTM) or Canadian Digital Elevation Data (CDED), and which SAR mission is being processed; Radarsat-2 (RS2), Radarsat Constellation Mission (RCM) or Sentinel-1 (S1).

All individual config fields Table 1.

Table 1: Config fields

Field	Section	Purpose	Data type
DEM_dir	Directories	A location where DEM files are stored	Full Path
watch_folder	Directories	A location where SAR data to be processed is placed	Full Path
gsw_path	Directories	A location where GSW tiles for training are stored	Full Path
output	Directories	Where classified results (rast & vect) are placed	Full Path
tmp	Directories	Location for temporary files	Full Path
log_dir	Directories	Location for log files	Full Path
DEMType	Params	DEM product to use in preprocessing	SRTM or CDED
satellite_profile	Params	SAR sensor being processed	RS2, RCM, or S1
num_procs	Params	Number of processors to use during classification	int

## 2.3 SAR Data

The current version of SSWM (1.1) supports SAR data from the following missions: Radarsat-2, Radarsat Constellation Mission (RCM), and Sentinel-1. Functionality with Radarsat-2 has not been tested in this version however, thus, using this data is not guaranteed to produce accurate results. Additionally, the RCM preprocessor expects as input a multiband raster product (IE GeoTiff) that is pre-calibrated, thus the user is responsible for conducting this initial preprocessing. If this is unobtainable, it is recommended to use Sentinel-1 data, as the Sentinel-1 preprocessor performs all necessary preprocessing steps (including calibration) using OrfeoToolbox. There is currently no intention to add support for additional SAR missions, however, a new function in the preprocessor for any given SAR mission could be added by the user if desired. Simply utilize the Sentinel-1 preprocessor as a template.

## 2.4 OrfeoToolbox

SSWM utilizes OrfeoToolbox (OTB, <https://www.orfeo-toolbox.org/>) to perform some SAR preprocessing, mainly calibration and orthorectification of Sentinel-1 products. To install, download the latest build for your operating system from here: <https://orfeo-toolbox.org/packages/>, and unzip the contents to a permanent location. No installer needs to be run. While OrfeoToolbox does have a Python API, is it difficult to set up due to overlapping dependancies with pre-build Python environments. Instead, SSWM calls the necessary OTB functions via the command line. To do this, the full path to the OTB bin folder must be added as a system *Path* variable. For example, using OTB version 9.0.0 that was extracted to the C: drive on Windows, the following would need to be added to the system Path variable: **C:OTB-9.1.0-Win64bin**.

## 2.5 Computational Power

Many of the operations performed by SSWM are computationally intensive, something that is exacerbated when processing Sentinel-1 data given its resolution and scene size. Several setting within the Python scripts can be modified to improve performance and computation success:

- 1) For preprocessing completed using OrferToolbox, the amount of RAM available to the toolbox can be modified. OTB will automatically tile the data product for processing based on the amount of RAM that is available, thus, increasing or decreasing OTB's RAM allotment will dictate the speed of processing, but also makes it possible for less powerful systems to perform operations. Within the preprocessing.py script, a global 'MAX\_RAM' parameter has been defined. The current default value is 2500 MB.
- 2) After training, SAR scenes are classified in chunks to prevent memory overflow. This value is currently set to chunks of 1000 rows, and can be modified via the global parameter in launch\_forest.py. If execution of SSWM fails at this stage due to memory overflow, reduce this value.
- 3) The number of processor used during classification, which is set by the user in the config file, also dictates the speed

at-which scenes are processed. This should be modified in conjunction with the chunksize to find the ideal parameter set for processing on your specific machine.

## 2.6 GSW Tiles

The Global Surface Water dataset (GSW, doi:10.1038/nature20584) is used to train the random forest classifier. The dataset is global, and can be downloaded as a series of 10x10 degree tiles from here: <https://global-surface-water.appspot.com/download>. The user must download the occurrence product for each tile within their ROI, and place them into the waterTiles directory defined earlier.

NOTE: The scripts expect the GSW tiles in a specific naming convention (occurrence\_\*\*LongBoundary\*\*\_\*\*LatBoundary\*\*.tif, Ex. occurrence\_100W\_50N.tif). If the user finds the tiles to have a different naming convention, the tiles will have to be renamed to this convention in order for the scripts to run properly.

## 2.7 DEM Products

DEM files are used by the preprocessor for orthorectification of the SAR scenes. The DEM tiles needed for each SAR scene are automatically downloaded if they are not already available within the DEM folder. Two DEM options are available; Shuttle Radar Topography Mission (SRTM) and Canadian Digital Elevation Data (CDED). Downloading CDED tiles does not require an account, however, they are only available within Canada, thus, if any portion of the SAR scene exists outside of Canada, strange behavior will occur. SRTM tiles are available globally to 60 degrees North, but require an EarthData account to access (<https://urs.earthdata.nasa.gov/>). If any portion of the SAR data extends above 60N, strange behavior will occur. For Python to access EarthData products, a **.netrc** file is needed in the users Home directory. To make this, create a text file in your Home directory with the name **.netrc**, and add the following line to it:

```
machine urs.earthdata.nasa.gov login <username> password <password>
```

where <username> and <password> are your EarthData credentials.

## 2.8 Launching SSWM

Before running SSWM, ensure that the desired SAR scenes are placed into the water\_folder (keep the zipped). Next, open the check\_directory.py script, and add the full path to the config file (classify.ini) to the config variable (line 17). Then, run check\_directory.py using the Python environment created earlier.

## FUNCTIONS

### 3.1 Pre-Process

`SSWM.preprocess.preprocess.preproRCM_bd(folder, DEM_dir, cleanup=True, product='CDED', filter=True)`

Preprocess RCM scenes that have been converted to \*.tif files

This assumes files have been converted to (amplitude \* 20k) values and have embedded GCPs

*Parameters*

**folder**

[str] Path to data folder

**DEM\_dir**

[str] Path to directory containing DEM files in

**cleanup**

[boolean] Whether intermediate files should be deleted

**product**

[str] Which DEM product to use.

*Returns*

**str**

Path to zipped output files

`SSWM.preprocess.preprocess.preproRS2(product_xml, DEM_dir, cleanup=True, product='CDED')`

Preprocess Radarsat-2 file in preparation for classification

*Parameters*

**product\_xml**

[str] Path to product.xml file for Radarsat-2 image

**DEM\_dir**

[str] Path to directory containing DEM files in appropriate folder hierarchy

**cleanup**

[boolean] Whether intermediate files should be deleted

**product**

[str] Which DEM product to use.

*Returns*

**str**

Path to zipped output files

`SSWM.preprocess.preprocess.preproS1(folder, DEM_dir, cleanup=True, product='CDED')`

Preprocess Sentinel-1 file in preparation for classification

*Parameters*

**folder**

[str] Path to data folder

**DEM\_dir**

[str] Path to directory containing DEM files in appropriate folder hierarchy

**cleanup**

[boolean] Whether intermediate files should be deleted

**product**

[str] Which DEM product to use.

*Returns*

**str**

Path to zipped output files

This file contains functions to download and mosaic DEM tiles from a variety of providers

`SSWM.preprocess.DEM.NTS_tiles_from_extent(ext, scale=1)`

Determine which NTS tiles are required to cover a target spatial extent

*Parameters*

**ext**

[dict] Dictionary with the following keys: {xmin, xmax, ymin, ymax} corresponding to the spatial extent in WGS84 decimal degrees

scale : int

*Examples*

```
ext = {'ymin': 52, 'ymax': 53, 'xmin': -114, 'xmax': -112} NTS_tiles_from_extent(ext)
```

`SSWM.preprocess.DEM.SRTM_tile_name(lon, lat)`

Build name of SRTM DEM file

*Parameters*

**lon**

[int] Longitude (whole number) for corner of DEM tile. Negative numbers correspond to W

**lat**

[int] Latitude (whole number) for corner of DEM tile. Negative numbers correspond to

*Returns*

**str**

File name of DEM tile for SRTM

*Example*

```
SRTM_tile_name(-110, 49)
```

`class SSWM.preprocess.DEM.SessionWithHeaderRedirection(username, password)`

**rebuild\_auth(prepared\_request, response)**

When being redirected we may want to strip authentication from the request to avoid leaking credentials. This method intelligently removes and reapplies authentication where possible to avoid credential loss.



```
SSWM.preprocess.DEM.create_DEM_mosaic(DEM, DEM_dir, dstfile, product='CDED', vrt_only=False,
                                       format='GTiff')
```

Create a Mosaic from a list of DEM urls or NTS tiles. Missing tiles will be downloaded

```
SSWM.preprocess.DEM.create_DEM_mosaic_from_extent(ext, dstfile, DEM_dir, product='CDED',
                                                  vrt_only=False)
```

Generate DEM mosaic covering a extent

#### Parameters

##### **ext**

[dict] Dictionary with the following keys: {xmin, xmax, ymin, ymax} corresponding to the spatial extent in WGS84 decimal degrees

##### **dstfile**

[str] Path to file to create

##### **DEM\_dir**

[str] Directory where DEM files are saved

##### **product**

[str] DEM source to use. One of ("SRTM", "CDED").

##### **vrt\_only**

[boolean ] Whether to create a VRT as an output file or

#### Returns

##### **str**

Path to mosaicked DEM

#### Examples

```
from os import path home = path.expanduser('~') ext = {'ymin': 52, 'ymax': 53, 'xmin': -114, 'xmax': -112}
create_DEM_mosaic_from_extent(ext,
                              dstfile = path.join(home, 'mosaic.tif'), DEM_dir = path.join(home, 'DEM'), product = "CDED",
                              vrt_only = False)
```

```
SSWM.preprocess.DEM.degree_tiles_from_extent(ext, tile_function, xoff=0, yoff=0)
```

Get a list of raster tiles required to cover a spatial extent

#### Parameters

##### **ext**

[dict] Dictionary with the following keys: {xmin, xmax, ymin, ymax} corresponding to the spatial extent in WGS84 decimal degrees

##### **tile\_function**

[function] function that takes lon, lat as keyword arguments and returns tile name

#### Returns

##### **list**

List of tile names required to cover specified spatial extent

#### Examples

```
E = {'xmin': -110, 'xmax': -108, 'ymin': 48, 'ymax': 51 }
```

```
SSWM.preprocess.DEM.downloadSRTM(url, dstfile, username=None, password=None, retry=5)
```

Downloads an SRTM tile.

#### Parameters

**url**

[str] path to SRTM tile

**username**

[str (optional)] USGS Earthdata username. If missing, looks for the existence of a .netrc file in your home directory

**password**

[str (optional)] USGS Earthdata username. If missing, looks for the existence of a .netrc file in your home directory

**retry**

[int] how many times to retry downloading

**If username / password are not provided, the function requires a netrc**

file in your home directory (named either ‘\_netrc’ or ‘.netrc’)

with the following contents: machine <hostname> login <login> password <password>

SSWM.preprocess.DEM.**download\_and\_unzip**(url, destfile, exdir, rmzip=True)

Downloads and unzips a file

*Parameters***url**

[str] Url path

**destfile**

[str] Filepath of output zipfile

**exdir**

[str ] The directory to which files are extracted

**rmzip**

[boolean] Whether or not to remove zipfile after extraction.

*Returns***str**

path(s) to target tiles

SSWM.preprocess.DEM.**download\_multiple\_DEM**(DEM, DEM\_dir, product='CDED')

Download a list of DEM URLs. If they exist already, they are not downloaded

*Parameters***DEM**

[list] List of DEM urls (SRTM) or NTS tiles (CDED)

**DEM\_dir**

[str ] Path to which files are downloaded

**product**

[str] Which DEM tile series should be downloaded: ('SRTM', 'CDED')

*Returns***list**

a list of file paths for target DEMs

SSWM.preprocess.DEM.**download\_single\_DEM**(DEM\_id, DEM\_dir, replace=False, product='CDED')

Download a DEM tile

*Parameters*

**DEM\_id**

[str] Name or NTS sheet of tile to download. If product is “SRTM”, a name should be specified, but if product is “CDED”, then a NTS sheet should be.

**DEM\_dir**

[str ] Path to which files are downloaded

**replace**

[boolean] Whether or not existing files should be re-downloaded and overwritten

**product**

[str] Which DEM tile series should be downloaded: (‘SRTM’, ‘CDED’)

*Returns***list**

List of file paths to DEM files. There may be more than one file per single zipped tile.

**SSWM.preprocess.DEM.egm96\_to\_wgs84\_heights**(*dem, geoid*)

Convert heights above the EGM96 geoid to heights above the WGS84 ellipsoid, for example, as required to use the RADARSAT-2 rational function model.

**SSWM.preprocess.DEM.get\_spatial\_extent**(*raster\_path, target\_EPSG=4326, tol=0.5*)

Get the spatial extent of a raster file.

If the file is not georeferenced (e.g. for raw radarsat 2), this function attempts to use the GCPs in the image . However, this doesn’t always produce exact results, so it is advisable to use an extra buffer tolerance in your spatial extent (maybe ~0.1 decimal degrees)

*Parameters***raster\_path**

[str] Path to raster for which a spatial extent is desired

**target\_EPSG**

[int] EPSG code specifying coordinate system for output file

**tol**

[float ] By how many decimal degrees to buffer spatial extent

*Returns***dict**

Dictionary with the following keys: {xmin, xmax, ymin, ymax} corresponding to the spatial extent in WGS84 decimal degrees

**SSWM.preprocess.DEM.get\_tile\_path\_CDED**(*NTS*)

Get FTP path for a CDED NTS tile

*Parameters***NTS**

[str] Name of NTS sheet for which a DEM is desired

*Returns***str**

FTP location for CDED DEM tile

### 3.1.1 Example

```
get_tile_path_CDED("079D01") get_tile_path_CDED("079D")
```

```
SSWM.preprocess.DEM.get_tile_path_SRTM(-110, 49)
```

```
SSWM.preprocess.filters.enhanced_lee_filter(img, looks, window=7, df=1)
```

Apply enhanced lee filter to image. Does not modify original.

Enhanced lee filter following Lopes et al. (1990) (PCI implementation)

*Parameters*

**img**

[numpy array ] Array to which filter is applied

**window**

[int] Size of filter

**looks**

[int] Number of looks in input image

**df**

[int] Number of degrees of freedom

*Returns*

array

**R = Im for Ci <= Cu**

$R = I_m * W + I_c * (1 - W)$  for  $C_u < C_i < C_{max}$   $R = I_c$  for  $C_i \geq C_{max}$  where:  $W = \exp(-(C_i - C_u) / (C_{max} - C_i))$   $C_u = \text{SQRT}(1 / \text{Number of Looks})$   $C_i = S / I_m$   $C_{max} = \text{SQRT}(1 + 2 / \text{Number of Looks})$   $I_c$  = center pixel in the kernel  $I_m$  = mean value of intensity within the kernel  $S$  = standard deviation of intensity within the kernel

```
SSWM.preprocess.filters.filter_image(img, output=None, filter='lee', **kwargs)
```

*Parameters*

**file**

[str][ ] File to filter (may have multiple bands)

**filter**

[str ] Name of filter to use on each band

**output**

[str ] Path to output file. If none, overwrites input file

```
SSWM.preprocess.filters.lee_filter(img, window=(5, 5))
```

Apply a Lee filter to a numpy array. Modifies original array

*Parameters*

**img**

[numpy array ] Array to which filter is applied

**window**

[int] Size of filter

```
SSWM.preprocess.filters.lee_filter2(img, window=(3, 3))
```

Apply a Lee filter to a numpy array. Does not modify original.

Code is based on: <https://stackoverflow.com/questions/39785970/speckle-lee-filter-in-python>

PCI implementation is found at [http://www.pcigeomatics.com/geomatica-help/references/pciFunction\\_r/python/P\\_fle.html](http://www.pcigeomatics.com/geomatica-help/references/pciFunction_r/python/P_fle.html)

#### *Parameters*

##### **img**

[numpy array ] Array to which filter is applied

##### **window**

[int] Size of filter

#### *Returns*

##### **array**

filtered array

`SSWM.preprocess.filters.moving_window_sd(data, window, return_mean=False, return_variance=False)`

This is Ben's implementation Calculate a moving window standard deviation (and mean)

`SSWM.preprocess.filters.window_stddev(img, window, img_mean=None, img_sqr_mean=None)`

Calculate standard deviation filter for an image

#### *Parameters*

##### **img**

[numpy array ] Array to which filter is applied

##### **window**

[int] Size of filter

##### **img\_mean**

[array, optional] Mean of image calculated using an equally sized window. If not provided, it is computed.

##### **img\_sqr\_mean**

[array, optional] Mean of square of image calculated using an equally sized window. If not provided, it is computed.

The function is based on code from: [http://nickc1.github.io/python/matlab/2016/05/17/Standard-Deviation-\(Filters\)-in-Matlab-and-Python.html](http://nickc1.github.io/python/matlab/2016/05/17/Standard-Deviation-(Filters)-in-Matlab-and-Python.html)

`SSWM.preprocess.orthorectify.orthorectify_dem_rpc(input, output, DEM, dtype=None)`

Orthorectify raster using rational polynomial coefficients and a DEM

#### *Parameters*

##### **input**

[str] Path to image to orthorectify

##### **output**

[str] Path to output image

##### **DEM**

[str] Path to DEM

##### **dtype**

[int] GDAL data type for output image (UInt16=2, Float32=6 etc.)

#### *Returns*

##### **boolean**

True if it completes successfully

`SSWM.preprocess.orthorectify.orthorectify_otb(input, output, DEMFolder, gridspacingx, ram=1000)`

Orthorectify raster using orfeotoolbox Ortho

### 3.1.2 Parameters

**input**

[str] Path to image to orthorectify

**output**

[str] Path to output image

**DEM**

[str] Path to DEM

**gridspacing**

[float] pixel size of deformation grid used for the ortho

### 3.1.3 Returns

`SSWM.preprocess.preutils.ProcessSLC(product_xml)`

Convert SLC values to raw DN values

Checks whether a RS-2 product.xml file is associated with SLC data and if so, converts the two-channel (i,q) \*.tif images into single-channel (amplitude) images. Also updates the product.xml file data type attribute from 'Complex' to 'Magnitude Detected'

*Parameters*

**product\_xml**

[str] file path pointing to product.xml file

*Returns*

**boolean**

True if completed successfully

**class** `SSWM.preprocess.preutils.RCM`

Class for accessing information about an RCM dataset

**classmethod** `path_to_xml(folder)`

given a standard folder with RCM data, find the product.xml file

**class** `SSWM.preprocess.preutils.RS2`

Class for accessing information about an RS2 dataset

**classmethod** `lut(product_xml, norm='Sigma')`

given product\_xml path, find calibration LUTs norm : str

one of 'Beta', 'Gamma', 'Sigma' (default)

**classmethod** `path_to_xml(folder)`

given a standard folder with RS-2 data, find the product.xml file

**classmethod** `product_xml_imagery_files(xml)`

Return a list of which imagery files are associated with a RS-2 product.xml file

**classmethod** `product_xml_pol_modes(xml)`

Return a list of polarization modes associated with an RS-2 product.file

**class** `SSWM.preprocess.preutils.Radar`

Generic class for RS2 and RCM folder structures

**classmethod** `TIF_channels(tif)`

Get count how many channels are in an image

**SSWM.preprocess.preutils.ReIm2Amp**(*re, im, inplace=True*)

Convert complex components to their modulus

Adds small value to the result to ensure it is positive because the code is based on the SLC2IMG algorithm from PCI such that  $DN = \text{int}(\sqrt{I*I + Q*Q} + 0.5)$

*Parameters*

**re**

[numpy array] Numpy array of shape (m,n) corresponding to the real component of a complex number.

**im**

[] Numpy array of shape (m,n) corresponding to the imaginary component of a complex number.

**inplace**

[boolean] Whether the inputs should be modified in-place. If true, the final result is stored in the re array

*Returns*

**array**

Modulus of real and imaginary arrays (with shape [m,n])

**class SSWM.preprocess.preutils.S1**

Class for accessing information about an RCM dataset

**SSWM.preprocess.preutils.SLC2IMG**(*image\_file, output*)

Convert SLC (Re, Im) raster to amplitude.

The code is based on the SLC2IMG algorithm from PCI such that  $DN = \text{int}(\sqrt{I*I + Q*Q} + 0.5)$

*Parameters*

**image\_file**

[str ] Path to imagery file, usually a tiff

**output**

[str] Path to output file

**SSWM.preprocess.preutils.calibrate**(*array, lut, complex=False, scale=20000*)

apply LUT calibration to a radar array. Modifies array in-place

*Parameters*

**array**

[array-like] m x n array of raw DN values or modulus for SLC  $(DN_i^{**2} + DN_q^{**2})^{**0.5}$

**lut**

[str] path to xml for LUT

**complex**

[bool] does the array represent the modulus of complex (SLC) data?

**scale**

[int] scaling factor used to store results as int16 (default is 20000, same as CIS for visual interpretation)

**SSWM.preprocess.preutils.calibrateS1**(*img, lut='sigma'*)

Using OrfeoToolbox, calibrate an S1 product. Calibration is performed per data band, and are then stacked.

**SSWM.preprocess.preutils.calibrate\_in\_place**(*file, lut, complex, scale, band=[1]*)

Apply LUT calibration to file and change in-place

`SSWM.preprocess.preutils.cloneRaster(img, newRasterfn, ret=True, all_bands=True, coerce_dtype=None, copy_data=False)`

make empty raster container from gdal raster object. Does not copy data

*Parameters*

**img**

[osgeo.gdal.Dataset] An open gdal raster object

**newRasterfn str**

Filename of raster to create

**ret**

[boolean] Whether to return a file handle. If False, closes file

**all\_bands**

[boolean] Whether or not all bands should be copied or just the first one

*Returns*

a handle for the new raster file (if ret is True)

`SSWM.preprocess.preutils.copy_band_metadata(src, dst, bands)`

Copy band metadata from one osgeo.gdal.Dataset to another

*Parameters*

**src**

[osgeo.gdal.Dataset] An open gdal raster object

**dst**

[osgeo.gdal.Dataset] A gdal raster object that is open for writing

**bands**

[int] How many bands are in the image

`SSWM.preprocess.preutils.copy_georeferencing(src, dst)`

Copy geotransform and/or GCPs from one osgeo.gdal.Dataset to another

*Parameters*

**src**

[osgeo.gdal.Dataset] An open gdal raster object

**dst**

[osgeo.gdal.Dataset] A gdal raster object that is open for writing

`SSWM.preprocess.preutils.copy_metadata(src, dst)`

Copy metadata from one osgeo.gdal.Dataset to another

*Parameters*

**src**

[osgeo.gdal.Dataset] An open gdal raster object

**dst**

[osgeo.gdal.Dataset] A gdal raster object that is open for writing

`SSWM.preprocess.preutils.createvalidpixrast(img, dst, band)`

Create valid pixel raster (0 or 1) for a gdal raster band

`SSWM.preprocess.preutils.get_blocksize_options(img)`

Get raster blocksize information as a string that can be passed to gdal



`SSWM.preprocess.preutils.incidence_angle_from_gains(beta_gains, sigma_gains, complex=False)`  
 calculate incidence angle array

`SSWM.preprocess.preutils.incidence_angle_from_xml(beta_xml, sigma_xml, nrow, complex=False)`  
 Calculate incidence angle from lutBeta and lutSigma xml files

*Parameters*

**beta\_xml**

[str] path to lutBeta.xml file

**sigma\_xml**

[str] path to lutSigma.xml file

**nrow**

[int] number of rows in output array (number of lines in original image)

**complex**

[boolean] whether or not the xml files represent complex data (in which case beta and sigma values are squared before dividing)

*Returns*

an array of dimension (M,N) with M = nrow and N = the number of values represented by each the xml files.

`SSWM.preprocess.preutils.interpolate_steps(array, step)`  
 interpolate array with desired step size

`SSWM.preprocess.preutils.interpolator(y)`  
 Interpolate missing (nan) values in an array

*Parameters*

**y**

[array] Array which may contain nan values

*Returns*

**array**

equal-length array with nan values replaced with imputed data

*Example*

import numpy as np  
 a = np.array([1, np.nan, np.nan, 4, np.nan, 6, 7], dtype='float32')  
 interpolator(a)

`SSWM.preprocess.preutils.read_calibration_gains(xml)`  
 Read calibration info from RCM or RS2 lut\*.xml

*Parameters*

**xml**

[str] Path to look-up table (e.g. sigma.xml)

*Returns*

**tuple**

tuple consisting of: (1) gains (array) (2) offset (int) (3) stepsize (int)

`SSWM.preprocess.preutils.reproject_image_to_master(master, src, dst)`

This function reprojects an image (src) to match the extent, resolution and projection of another (master) using GDAL. The newly reprojected image is a GDAL VRT file for efficiency. A different spatial resolution can be chosen by specifying the optional res parameter. The function returns the new file's name.

*Parameters*

**master: str**

A filename (with full path if required) with the master image (that that will be taken as a reference)

**src: str**

A filename (with path if needed) with the image that will be reprojected

**res: float, optional**

The desired output spatial resolution, if different to the one in master.

*Returns*

The reprojected filename

code credit: [https://github.com/jgomezdans/eoldas\\_ng\\_observations](https://github.com/jgomezdans/eoldas_ng_observations)

```
SSWM.preprocess.preutils.write_array_like(img, newRasterfn, array, dtype=6, ret=True, driver='GTiff',
                                           copy_metadata=False)
```

write numpy array to gdal-compatible raster.

*Parameters***img**

[osgeo.gdal.Dataset or str] An open gdal raster object or path to file

**newRasterfn**

[str ] Filename of raster to create

**array**

[array] array to be written with shape (nrow[y], ncol[x], band)

**dtype**

[int ] What kind of data should raster contain?

**ret**

[logical ] Whether to return a file handle. If false, closes file

*Returns***osgeo.gdal.Dataset**

a handle for the new raster file

## 3.2 Random-Forest

```
class SSWM.trainingTesting.GSWInterpolator.GSWInterpolator(sat_f_name, gsw_dir,
                                                           output_dir=None, data=None,
                                                           use_cols_vector=None)
```

Handle Global Surface Water files

*Parameters***sat\_f\_name**

[str] File path to satellite imagery scene for which water mask is to be interpolated

**gsw\_dir**

[str] File path to location of global surface water \*.tif files

**output\_dir**

[str] File path to desired location of output files

data : use\_cols\_vector :

**get\_covering\_global\_surface\_water\_file\_names**(*min\_lat, max\_lat, min\_lon, max\_lon*)

Assuming we're running in the path where there is a 'coverage' directory containing all the RS2 BBOX and convex hulls.

**class** SSWM.trainingTesting.PixStats.PixStats(*f\_path, output\_dir=None, gsw\_path=None, images\_output\_dir=None, fst\_converter\_path=None*)

Get satellite images ready for neural net processing

*Parameters*

**f\_path**

[str] imagery file to be converted

output\_dir : str

**gsw\_path**

[str] Path to directory containing global surface water data

images\_output\_dir : str

**fst\_converter\_path**

[str ] File path with location to save the files in FST format

**classmethod** get\_file\_pol(*file*)

get valid polarizations for a file

**get\_stats\_and\_sample**(*valseed, nwater, nland, max\_L2W\_ratio, write\_water\_mask=False*)

Sample an image, we no longer use H5 files

**get\_valid\_bands**()

build dictionary to describe order of bands

For RandomForest water classification of radar images

**class** SSWM.forest.forest.imgchunker(*img, by\_y=5000*)

Splits image into chunks for memory-safer processing

This object takes raster arrays of dimension (m,n,p) and yields 'chunks' with dimension (i, j) with  $1 < i < m \cdot n$  and  $1 < j < p$ . The smaller chunks can then be classified without running out of memory.

The last chunk is usually smaller than the rest unless by\_y is chosen to evenly divide the number of image rows.

*Parameters*

**img**

[str ] Path to gdal-compatible raster image

**by\_y**

[int] How many rows should be returned during each iteration

**build\_band\_dict**(*img*)

Get indices of image bands that will be used in classification

**chunkerator**()

Generate image chunks for classification

During the classification process, this function 'feeds' the classifier pieces of the input image. The last piece of the image is usually smaller than the rest.

*Yields*

**tuple**

A tuple containing (1) An array corresponding to a chunk of the input image, and (2) the y-offset of the chunk relative to the upper-left corner of the original image.

**static get\_chunk**(*img, ix, offx, offy, lnx, lny*)

Get a slice of an image for classification.

Images are classified in pieces to prevent memory overflow

*Parameters***ix**

[list ] indices (1-based) for image bands that are to be used.

**offx**

[int] X offset from which to begin reading image. Referenced to upper left corner

**offy**

[int] Y offset from which to begin reading image. Referenced to upper left corner.

**lnx**

[int] How many columns to read beginning from x offset

**lny**

[int] How many rows to read beginning from y offset

*Returns***array**

an array corresponding to a slice of the raster array with dimensions (m,n,p) where m=lnx, n=lny and p=len(ix)

**open**(*img*)

Open an image and collect some parameters

**reshape\_chunk**(*chunk*)

Flatten a 3-d array so it can be fed into a random forest classifier

*Parameters***chunk**

[array-like ] 3-d array with dimensions (m, n, p)

*Returns***array-like**

2-d array with dimensions (m\*n, p). Each row corresponds to a pixel and each column corresponds to an image band

**class SSWM.forest.forest.metric**(*labels, predictions*)

A class to hold various statistics about a binary classification

*Parameters***labels**

[array-like (1-d)] vector of feature labels

**predictions**

[array-like (1-d)] vector of predicted categories equal in length to labels

*Example*

```
labels = np.array([True, True, True, True, True, False, False, False])
predictions = np.array([True, False, False, True, True, True, False, False])
M = metric(labels, predictions)
print(M)
```

**add\_dict**(*dct, name*)

Add custom statistics

Dictionaries are added to the 'extras' attribute are written to the output file when save\_report() is called.

*Parameters*

**dct**

[dict] Dictionary of statistics to add

**name**

[str] Header for set of statistics when it is written to a file

**calculate\_metrics**(*labels, predictions*)

Calculates accuracy, precision, F1, recall and specificity

**confusion\_matrix**(*labels, predictions*)

Build confusion matrix for labels and predictions

**save\_report**(*txtfile*)

Saves all calculated statistics to a textfile.

Includes confusion matrix, derived statistics (F1, Accuracy etc..) and any custom statistics that were added.

*Parameters*

**txtfile**

[str] path to output file

**class SSWM.forest.forest.training\_dataset**

A class to hold data for random forest training and evaluation.

Makes use of hdf5 files to store training data.

*Attributes*

**training\_data**

[array-like] features for training samples

**testing\_data**

[array-like] features for testing samples

**training\_targets**

[array-like] 1-d vector of feature labels for training samples

**testing\_targets**

[array-like] 1-d vector of feature labels for testing samples

**sample\_from\_image**(*cur\_file, exdir, gsw\_path, valseed, nland=1000, nwater=1000, eval\_frac=0.2, max\_L2W\_ratio=10*)

sample n & m pixels water and land pixels respectively from the scene, split into training and testing sets needed for RF

**Parameters**

**cur\_file**

[str] path to image file

**exdir: str**

path to dataset directory

**gsw\_path**

[str] path to gsw files needed to create mask for training

**valseed**  
[int] seed for random sampling

**nland**  
[int] number of land pixels to sample

**nwater**  
[int] number of water pixels to sample

**eval\_frac**  
[float] fraction between 0 and 1 that should be set aside for evaluation

**max\_l2w\_ratio**  
[int] maximum allowed ratio of land pixels to water pixels in the training dataset

**split\_sample**(*sample*, *eval\_frac*=0.2)  
Randomly split sample into training and test subsamples  
Returned samples are shuffled relative to the input sample  
*Parameters*

**sample**  
[array-like] an array of samples with dimension (m, n)

**eval\_frac**  
[numeric] fraction of rows to allocate to testing data  
*Returns*

**tuple**  
Two arrays with dimension (m - j, n) and (j, n) where  $j \sim \text{eval\_frac} * m$

**class SSWM.forest.forest.waterclass\_RF**(\*\**rfargs*)  
RandomForest classifier for open-water classification of (radar) images  
*Parameters*

**\*\*rfargs**  
[] keyword arguments passed to sklearn.ensemble.RandomForestClassifier

**evaluate**()  
Evaluate the current random forest model using current test data

**predict\_chunked**(*imfile*, *outfile*, *chunksize*=5000)  
Classify an image piece-by-piece to avoid running out of RAM  
*Parameters*

**imfile**  
[str] Path to input image file

**outfile**  
[str] Path to output raster containing probability of water

**chunksize**  
[int] How many rows to process at once during classification

**predict\_features**(*imfile*, *outfile*)  
Use current RF model to produce binary classification of an image

**predict\_probabilities**(*imfile*, *outfile*)  
Use current RF model to produce probabilistic classification of an image

**save\_evaluation(*file*)**

Save current evaluation statistics to a text file

**train\_from\_image(*cur\_file, exdir, gsw\_path, valseed, nland=1000, nwater=1000, eval\_frac=0.2*)**

Train a random forest by sampling directly from an image. Optionally set aside some of the sample for evaluation.

**Parameters****cur\_file**

[str] path to image file

**exdir: str**

path to dataset directory

**gsw\_path**

[str] path to gsw files needed to create mask for training

**valseed**

[int] seed for random sampling

**nland**

[int] number of land pixels to sample

**nwater**

[int] number of water pixels to sample

**eval\_frac**

[float] fraction between 0 and 1 that should be set aside for evaluation

Postprocessing for probability images generated using random forest classification

**SSWM.forest.postprocess.grow\_regions(*input, output, window=3, val=50*)**

Threshold water classification and grow lakes by 1 pixel

**SSWM.forest.postprocess.max\_filter\_inplace(*img\_path, band=1, size=3*)**

Run a maximum filter on a raster file and changes the values in-place

**SSWM.forest.postprocess.modefilter(*input, output, window=7*)**

Threshold water classification at 50% water likelihood

**SSWM.forest.postprocess.postprocess(*classified\_img, output\_poly, extrasTXT, window=7*)**

Postprocess a classified probability image to remove false positives

using a technique inspired by Bolanos et al. (2013)

**Parameters****classified\_img**

[str] path to classified probability image

**output\_poly**

[str] path to output GPKG file

**pythonexe**

[str] path to python executable

**gdalpolypath**

[str] path to gdal\_polygonize.py file

**extrasTXT**

[str] path containing RF model quality metrics

**window**

[int] window size to use for filtering (Default 7)

`SSWM.forest.postprocess.rasterize_inplace(rast, inshape, prefill=0)`

Overwrites a raster with the output of a polygon rasterization

*Parameters***rast**

[str] path to EXISTING raster file that will store values from rasterized

**inshape**

[str] path to vector dataset that will be rasterized

**prefill**

[int] Value to write to raster before writing polygonization result

`SSWM.forest.postprocess.raststats(inshape, raster)`

calculate mean and max value of a raster in each polygon

`SSWM.forest.postprocess.set_nodata(file, nodata=0)`

Set nodata value for raster file

*Parameters***file**

[str] path to EXISTING raster file

**nodata**

[numeric ] value to set as nodata for input raster

`SSWM.forest.postprocess.threshold(input, val=50)`

Threshold a raster image and return the new array



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