USER MANUAL FOR SEN-ET SNAP PLUGIN

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Contents

Preface

The purpose of the Sen-ET SNAP plugin is to enable estimation of actual evapotranspiration (and other land-surface energy fluxes) at field scale using Sentinel-2 (S2) and Sentinel-3 (S3) satellite observations as well as meteorological data available from Copernicus Climate Data Store. It was developed as part of the Sen-ET project (http://esa-sen4et.org/) and consists of open-source Python libraries and thin wrapper enabling execution from within SNAP graphical user interface (GUI).

In this document we give an introduction to the Sen-ET project and its objectives and we describe the input data, the processing flows and the produced outputs, including their accuracy limitations. This is followed by a brief description of the Sen-ET operators and their SNAP GUI and command line interface. Finally, we briefly present the theoretical basis behind the proposed methodology and describe its limitations.

Chapter 1

Introduction

1.1 Background

Accurate and spatially distributed estimates of evapotranspiration (ET) are increasingly important with the growing global population and economy putting strain on fresh water resources and food supplies. The utility of ET maps has been demonstrated in a variety of applications, ranging from water rights management, through drought and food shortage monitoring, to more efficient use of land and water in agriculture and crop stress assessment. Those applications are directly relevant for reaching at least two of the UN Sustainable Development Goals (SDGs): goal 2 - zero hunger, and goal 6 - clean water and sanitation; and could also prove useful in trying to achieve other SDGs (e.g. goal 15 - life on land).

The most efficient methods for deriving such ET maps at local (field), regional and global scales make use of remote sensing observations, particularly from satellite-based sensors since they provide a synoptic view at regular time intervals. Majority of remote sensing models that estimate actual (as opposed to potential) ET do so through the estimation of land surface energy fluxes. This requires both knowledge of the state of vegetation (e.g. leaf area index or fraction of green vegetation) and of land surface temperature (LST) which acts as one of the model boundaries. Therefore, remote sensing observations using both visible/near-infrared and thermal infra-red sensors serve as an important source of input data for such models.

There are existing ET datasets utilising remote sensing observations but none of them fully satisfies the need for an accurate, operational, and field-scale flux estimates. One of the widely available datasets is the MODIS Global Evapotranspiration Project (MOD16) which while being suitable for regional and/or scientific applications (with an 8-day temporal and 1-km spatial resolution) is not fulfilling the need of field-scale operational applications. Another ET dataset is provided by USDA-ARS using a range of satellite sensors ranging from geostationary GOES with a spatial resolution of 5 km, through MODIS at 1 km to Landsat at 60 m. However, this dataset is currently only produced over the continental United States. In addition, the two mentioned datasets rely on the MODIS sensors on board Terra and Aqua satellites which are already working past their designed lifetime. Another freely available ET dataset is provided by LSA SAF and uses geostationary observations (without using LST) from Meteosat Second Generation (MSG) to derive 30 minute and daily ET observations over the whole MSG disc. However, the spatial resolution of this product (3- 6 km) is also insufficient for field-scale applications. Finally, there are various

advanced modelling approaches which indirectly incorporate remote sensing observations, such as ECMWF or GLDAS models, but the spatial resolution of their outputs is even coarser.

The recent launches of the Sentinel-2A , Sentinel-2B and Sentinel-3A satellites (and upcoming launch of Sentinel-3B) present new opportunities for accurate and operational modelling of actual ET with the use of remote sensing data. The Sentinel satellites were designed with the aim of serving operational needs of diverse user communities and fields of application. In the field of agriculture this aim is already partially realized with ESA projects such as "Sentinel-2 for Agriculture" providing a system which utilises high spatial and temporal resolution optical data from Sentinel-2 satellites (and Landsat-8) for estimating growing area extent for main crop types as well as crop status from temporal evolution of Leaf Area Index (LAI) over a growing season. Time-series of Sentinel-1 Synthetic Aperture Radar observations have also been used to operationally map rice crop evolution or to discriminate between different crop types. Sentinel-3 satellite has added the capacity of acquiring thermal observations to the existing suite of Sentinels' capabilities. This should allow for operational modelling of ET and of other land surface energy fluxes. However, for many agricultural applications the resolution of the modelled fluxes should be smaller than the typical field size. In the European Union agricultural context, where the Agricultural Census 2010 reported that an average farm size was 14.2 hectares and that 6 million farms were smaller than 2 hectares, this requires model outputs with a pixel size on the order of tens of meters. This is not possible when using Sentinel-3 alone (Sentinel-3 thermal sensor SLSTR has a spatial resolution of 1000 m) but might be achievable if synergies between Sentinel-3 and Sentinel-2 are exploited. In particular the Multi Spectral Instrument (MSI) on board Sentinel-2, with its high spatial resolution (up to 10 m) and red-edge spectral bands, could allow for disaggregation of ET model inputs and/or outputs to higher spatial resolution. By utilising the synergies between the sensors of those two satellites it might be possible to derive accurate flux estimates at high spatial resolution.

1.2 Objectives

The goal of this project is to develop an open-source software application for accurate, pre-operational modelling of instantaneous evapotranspiration (and other land-surface energy fluxes) at high (tens of meters) and medium (1 km) spatial resolutions with the use of observations coming from Sentinel-3 (medium resolution thermal and optical) and Sentinel-2 (high resolution optical) satellites. The project will focus on agricultural applications of ET but will also involve evaluating the model output in other land-covers (e.g. forest). The fluxes should be modelled at the highest possible spatial resolution without sacrificing the output accuracy.

An additional objective is to provide inputs for requirements gathering and design processes of a possible future ESA thermal mission. The focus of those inputs should be on ET estimation (and other related agricultural applications) and they should highlight the possibilities provided by, and limitations of, the current observational capabilities provided by the Sentinel constellation.

Those objectives were achieved through:

- Reviewing of existing methodologies for estimation of ET and for bridging the spatial gap between S2 and S3 observations.
  http://esa-sen4et.org/outputs/methodology-review/

- Prototyping and benchmarking the most promising approaches and evaluating the outputs in a number of ecosystems.
  http://esa-sen4et.org/outputs/prototype-benchmarking/

- Fully implementing the best performing approach as an open-source software application.
  http://esa-sen4et.org/outputs/software/

Chapter 2

Overview

2.1 Input data

The Sen-ET plugin is driven almost exclusively by Copernicus data sources. The primary inputs are based on optical data from Sentinel-2 MSI sensor and thermal data from Sentinel-3 SLSTR sensor as well as ERA-5 reanalysis meteorological dataset. In addition, a landcover map and a digital elevation model (DEM) are used as ancillary datasets.

The **Sentinel-2 MSI optical data** is used to characterize the biophysical state of the land surface at 20 m resolution. This resolution was selected because it corresponds to the native resolution of red-edge and shortwave-infrared MSI bands which are critical for the SNAP biophysical processor. It is also sufficient to capture most landscape features of interest (e.g. agricultural fields and meadows). The MSI data is also be used to sharpen the lower resolution SLSTR data. The Sentinel-2 images can be download from the Copernicus Open Access Hub (COAH - `https://scihub.copernicus.eu/`) from within SNAP using one the pluginÂ's operators. The plugin is designed to work with L2A (atmospherically corrected) data. However, for historical analysis L1C data might need to be used since historical L2A images are not always available in COAH. In those cases, users can download L1C images directly from COAH and perform the atmospheric correction using SNAP and Sen2Cor before continuing with Sen-ET plugin.

The **Sentinel-3 SLSTR thermal data** is used to establish the bottom boundary condition of the land surface energy model. The Sentinel-3 SLSTR images are available from the COAH and can be downloaded from within SNAP using the same Sen-ET operator as for Sentinel-2 image download. The plugin is designed to work with L2 SLSTR data, i.e. with the land surface temperature (LST) product. Since LST is acquired at around 1 km spatial resolution, it is sharpened using a machine-learning model to 20 m using another Sen-ET operator before being used within the evapotranspiration (ET) model. The Sentinel-3 acquisition does not have to be at the same time as the Sentinel-2 one and the two acquisitions could be separated by up to 10 days. The land-surface energy fluxes are always modelled at the time of S3 overpass. This is because changes in vegetation are not as dynamic as the changes in LST. However, the smaller the temporal difference between the two overpasses the smaller the chance of abrupt changes to vegetation conditions (e.g. harvest) introducing errors into the model.

The **meteorological data** is required to establish conditions which drive (e.g. air temperature) and modulate (e.g. wind speed) the energy transfer between the surface

and the atmosphere and consists of fields from ECMWF ERA-5 reanalysis dataset. This dataset is available for download from the Copernicus Climate Data Store (CDS - `https://cds.climate.copernicus.eu`) and this is from where it can be retrieved from within SNAP using Sen-ET operator. The users have to already be registered on CDS and have the API key file placed in the correct location (see `https://cds.climate.copernicus.eu/api-how-to#install-the-cds-api-key`). ERA-5 is produced with around 2-3 month delay and a number of product types are available. Sen-ET plugin uses the ensemble mean product which should ensure highest accuracy of the meteorological data. The following data fields are used: 2m_temperature, 2m_dewpoint_temperature, surface_pressure, 100m_v_component_of_wind, 100m_u_component_of_wind, surface_solar_radiation_downward_clear_sky, surface_solar_radiation_downwards, z. Users are able to replace some or all of ERA-5 data with meteorological data coming from source specific to their application (i.e. from national meteorological services) but in this case they are responsible for making sure that the data is saved in the correct format.

Land cover map is used to set parameters which are not easily retrievable from optical images, e.g. vegetation height. This is done using a look-up table (LUT) containing the parameter values for each land cover class. The LUT provided with Sen-ET plugin assumes a land cover map with a legend based on the UN Land Cover Classification System (LCCS). ESA's Climate Change Initiative land cover map utilises this legend and is available in SNAP using the AddLandCover operator. Users are able to use other land cover maps more suitable to their area of interest (e.g. Corine for European applications) but in that case they are required to create the LUT corresponding to the legend of the map which they are using. This can be easily done by creating or modifying a text file.

The last dataset which is used by the SEN-ET software is a digital elevation model (STRM DEM). It is used for adjusting air temperature to the correct elevation (100 m above ground) and optionally to take elevation and solar illumination conditions into account when sharpening LST. In both cases the DEM can be obtained using an existing AddElevation SNAP operator.

2.2 Processing flows

The main Sen-ET plugin processing chains are illustrated in Figure 2.1 (Sentinel-2 data pre-processing), Figure 2.2 (Sentinel-3 data pre-processing), Figure 2.3 (ERA-5 data pre-processing) and Figure 2.4 (land-surface energy flux modelling). They consist of Sen-ET operators and operators already existing in SNAP collected in graph processing framework (GPF) graphs.

To start **Sentinel-2 pre-processing** (Figure 2.1) the user has to specify an area of interest (AOI) as a geojson file and a start and end date for L2A images to be searched for in COAH. If requested images are found they are automatically downloaded. The user needs to run the L2A image through two provided GPF graphs consisting of existing SNAP functionality: first to estimated biophysical properties and two extract the cloud mask, and second to extract reflectance bands and sun zenith angle information from the L2A product. In both graphs, the data is first resampled to 20 m, since most of SNAP operators do not work with images containing different resolutions (as the original L2A image does). The mask file is then used as input to two other GPF graphs (any of the other files could also be used but mask is the smallest): first which downloads a DEM

and reprojects, resamples and subsets it to the S2 image projection, resolution and extent, and second which does the same with a landcover map. The biophysical parameters are used as input to a number of Sen-ET operators: together with landcover to set structural parameters (e.g. vegetation height or leaf inclination angle), to estimate leaf reflectance and transmittance, together with sun zenith angle to estimate fraction of vegetation which is green and finally together with structural parameters to estimate surface aerodynamic roughness.

Sentinel-3 pre-processing (Figure 2.2) also starts with user specifying an AOI and a date range to search for L2 LST images on COAH, which are download if found. Since L2 LST comes as a swath image (as opposed to tile), it is then subset to the AOI and assigned projection using existing SNAP operators and split into LST product, a cloud mask product and observation geometry product. The geometry product is first reprojected, resampled and subset to the AOI image projection, resolution and extent and then used as input to the LST sharpening operator (which uses Data Mining Sharpener - see Section 4) together with Sentinel-2 reflectance, high-resolution DEM, cloud mask and the LST itself. The result is a 20 m representation of LST which can be used as input to the land-surface energy flux model.

ERA-5 pre-processing (Figure 2.3), similarly starts with specifying an AOI and a date range. The required meteorological data is then downloaded from CDS and saved in a NetCDF file with time specified as one of the dimensions using a Sen-ET operator. The air temperature needs to adjusted from representing the temperature 2 m above ground to representing temperature 100 m above ground. This is done using the DEM and lapse rate of moist air. This adjustment (and the use of 100 m wind speed) is required because due to the low spatial resolution of the meteorological data it is better to assume that it represents conditions above the blending height, i.e. at a height where direct influence of land surface on atmospheric conditions is weak. The meteorological data also needs to be resampled, reprojected and subset to the S2 scene resolution, projection and subset and temporally interpolated to the time of S3 overpass over the AOI. All of those operations are performed by a provided Sen-ET operator. The result is meteorological data ready to be used as input to the land-surface energy flux model.

Once all the input data is prepared it is used to **model the actual land-surface energy fluxes** (Figure 2.4) using Two Source Energy Balance model (see Section 4). The modelled fluxes include latent heat flux which is the (TSEB) energy used during evapotranspiration. The meteorological inputs and some parameters derived from S2 observations are first used to estimate the net shortwave radiation and the longwave irradiance. Those estimates are then used together with other S2 based parameters and sharpened LST to derive the energy fluxes at 20 m resolution: sensible heat flux (H), latent heat flux (LE), ground heat flux (G) and net radiation (R_n). Those fluxes represent the instantaneous conditions at the time of S3 overpass and are in units of Wm^{-2}. The instantaneous LE can then be converted to daily evapotranspiration, in units of mm/day, using the ratio instantaneous and daily solar irradiances. This is the final output of the Sen-ET plugin.
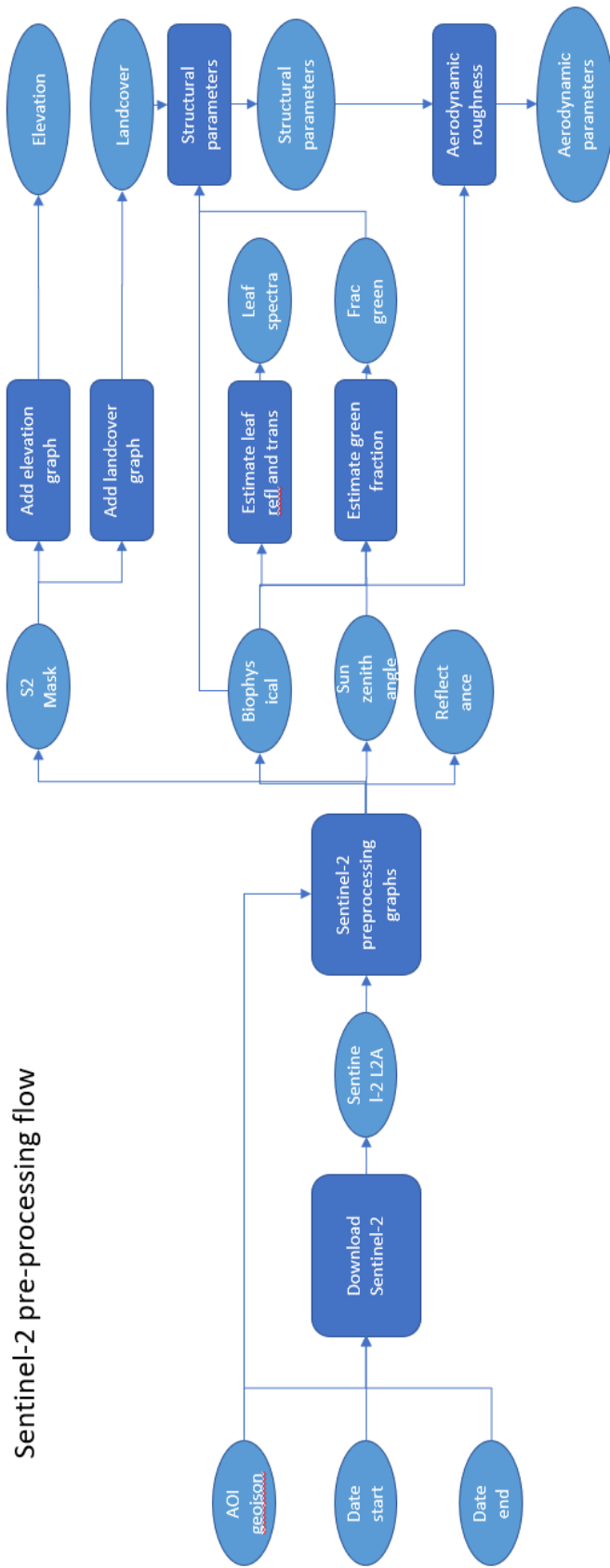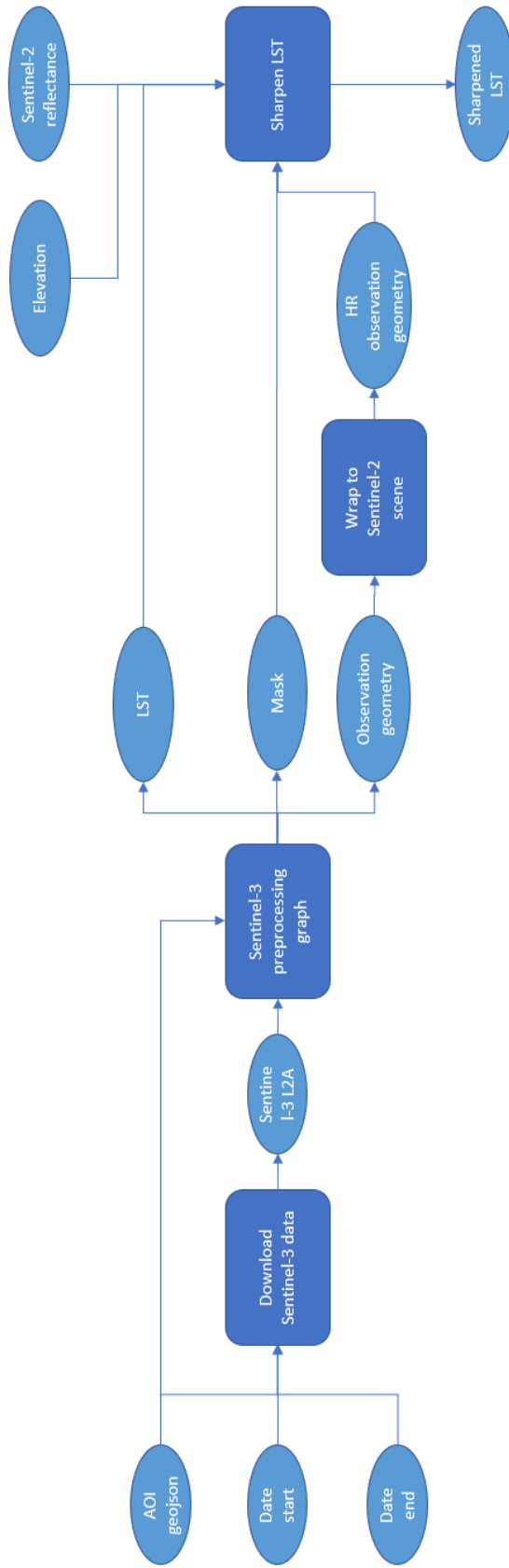
Figure 2.1: Processing flow for Sentinel-2 data, from downloading the data to preparing inputs required for evapotranspiration modelling. Ovals represent input and output data and rectangles represent processing steps

Figure 2.2: Processing flow for Sentinel-3 data, from downloading the data to preparing inputs required for evapotranspiration modelling. Ovals represent input and output data and rectangles represent processing steps.
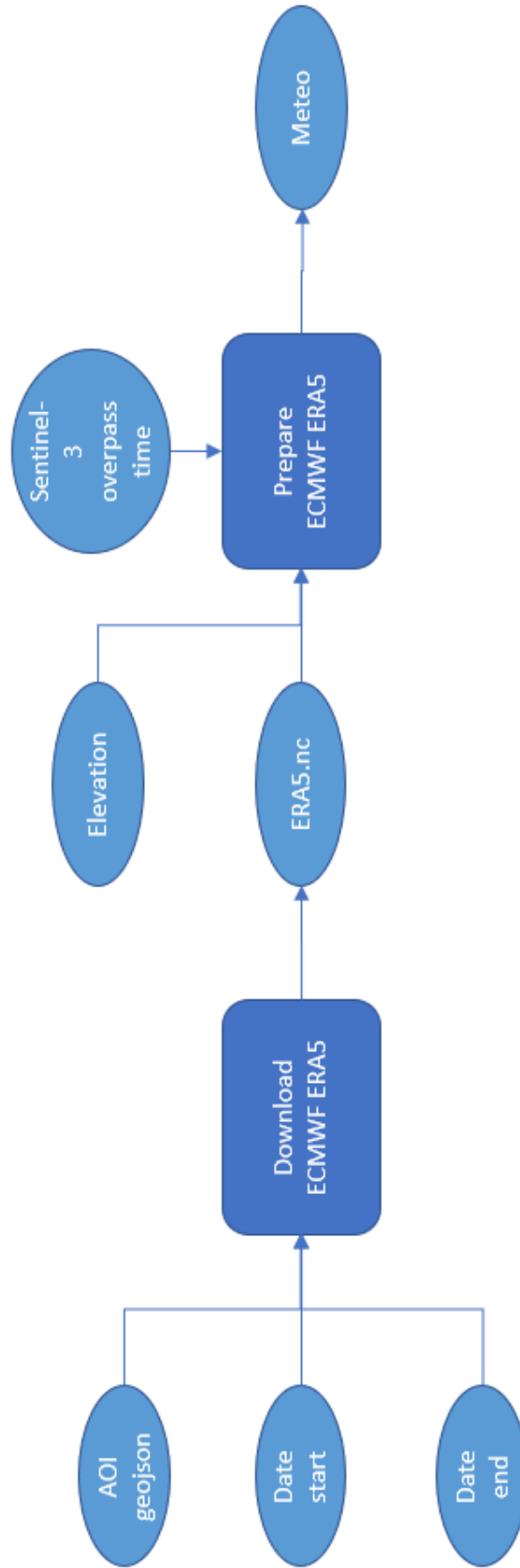
Figure 2.3: Processing flow for ECMWF meteorological data, from downloading the data to preparing inputs required for evapotranspiration modelling. Ovals represent input and output data and rectangles represent processing steps.
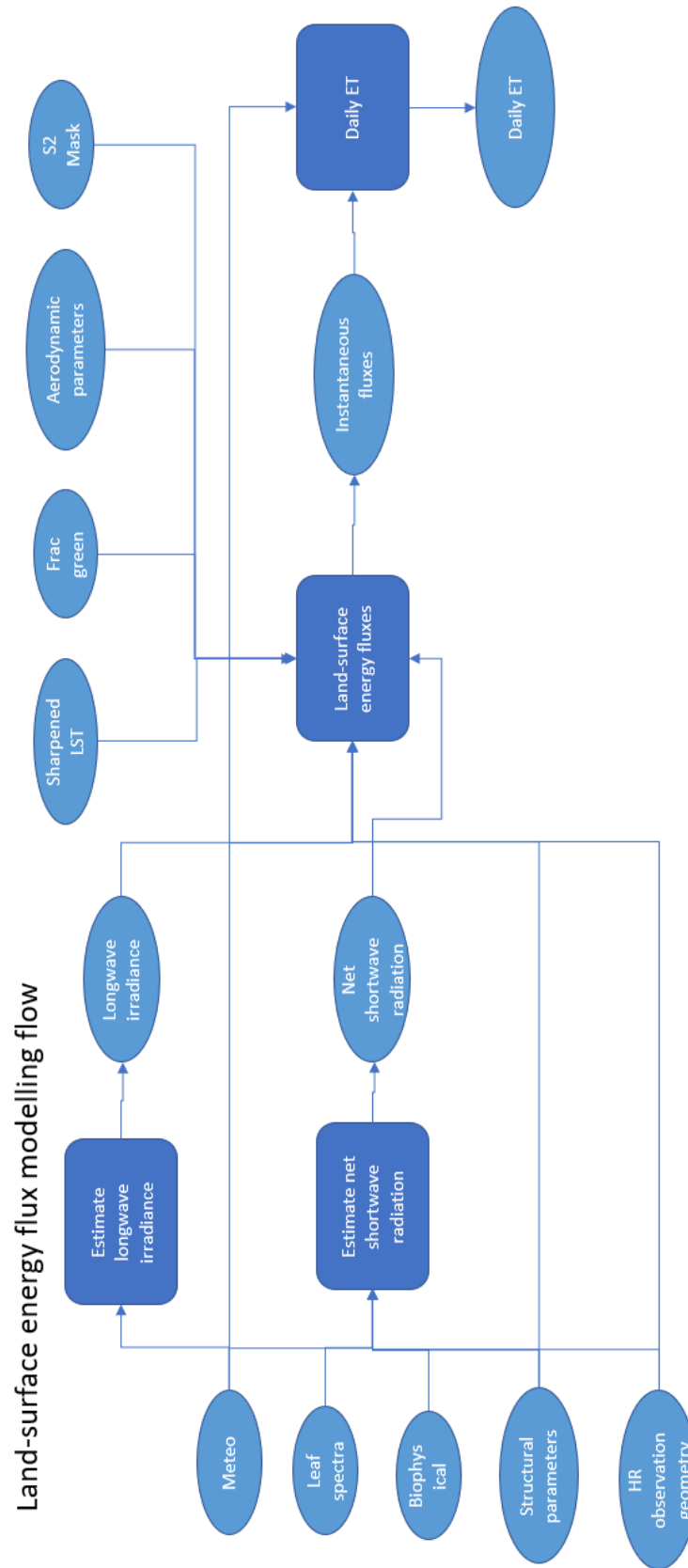
Figure 2.4: Processing flow for evapotranspiration modelling using prepared data derived from Sentinel-2, Sentinel-3 and ECMWF datasets. Ovals represent input and output data and rectangles represent processing steps.

2.3 Produced outputs

The main output of the Sen-ET plugin are the four modelled instantaneous land-surface energy fluxes: sensible heat flux (H), latent heat flux (LE), ground heat flux (G) and net radiation (R_n). The fluxes represent conditions at the time of Sentinel-3 overpass and are in Wm^{-2}. The latent heat flux is also converted to daily evapotranspiration, in mm/day, representing the total daily ET on the day of Sentinel-3 overpass.

On the land-surface, the **sensible heat flux** represents the temperature transfer from the surface to the overlying air (positive values) or the other way around (negative values). It is driven by the temperature difference between the surface and the air and modulated by surface (e.g. surface roughness) and meteorological (e.g. wind speed or atmospheric stability) conditions. Based on validation of the Sen-ET modelling approach in 11 sites spanning a range of land cover and climatic conditions, the expected relative root mean square error (rRMSE) of the modelled H is around 0.45 and the correlation (r) is around 0.67. In grasslands this improves to rRMSE of 0.37 and correlation of 0.79. It should be noted that the uncertainty in the turbulent fluxes (H and LE) measured at the validation sites is around 20% to 30%.

Latent heat flux represents the energy used to convert water from liquid to gas phase. This is the energy used in the process of evapotranspiration, i.e. water evaporation from the soil and transpiration from vegetation. It can be converted to the instantaneous amount of water evaporated (in mm/second) by dividing by the latent heat of vaporization. More usefully, this can then be converted to daily evapotranspiration in mm/day by multiplying by the ratio of instantaneous to average daily solar irradiance. Based on the same validation set as used for H, the expected rRMSE for LE is around 0.46 and r of 0.76 with best performance obtained in croplands (both herbaceous and woody) where rRMSE was 0.32 and r was 0.75.

Net radiation provides energy input for all the other fluxes. It is composed of net shortwave radiation (larger component) and net longwave radiation. The former depends on the solar irradiation and surface albedo while the latter on surface and air temperatures and emissivities. This flux is usually modelled quite accurately with the overall expected rRMSE of 0.11 and r of 0.93 with larger inaccuracies in semi-arid regions with limited vegetation cover.

Ground heat flux represents heat transfer from the surface to the deeper layers of the soil. It is usually the smallest of the four modelled fluxes and at the same time the one with largest uncertainty. This could be partially attributed to the high spatial variability of this flux combined with scale mismatch between field measurements (around tens by tens of centimetres) and model outputs (tens by tens of meters when modelled at high resolution). Validation resulted in rRMSE of 0.72 and r of 0.45 with the most accurate results in savannah ecosystem with rRMSE of 0.38 and r of 0.62 followed by grasslands with rRMSE of 0.42 and r of 0.68.

For more detailed validation results, users are encouraged to read the "Prototype benchmarking and description" document available from Sen-ET project website (`http://esa-sen4et.org/outputs/prototype-benchmarking/`) or the manuscript submitted to Hydrology and Earth System Sciences journal [1].

Chapter 3

Sen-ET SNAP Plugin

3.1 System requirements

The Sen-ET SNAP plugin is designed to process a whole Sentinel-2 scene and a corresponding subset of a Sentinel-3 LST product sharpened to Sentinel-2 resolution. The TSEB model requires many inputs and internal parameters. In addition, SNAP is quite resource-hungry, especially for memory. Therefore, even though the code has been optimized, it still requires substantial computing resources.

For deriving daily ET over a whole Sentinel-2 scene, around 20 GB of RAM is required. It is recommended to use a machine with at least 4 cores since some of the Sen-ET and SNAP operators execute across multiple processors. Around 2.5 GB of storage is required for the input Sentinel data. Throughout the pre-processing and modelling chains, temporary files amount to around 15 GB of storage. However, the final output, i.e. the map with daily ET covering the whole Sentinel-2 scene, only requires around 120 MB of storage. In addition, the Sen-ET plugin requires around 4 GB of disk space since it includes a self-contained Python environment holding all the required libraries, dependencies and binary files (see Section 3.2).

3.2 Installation

The Sen-ET SNAP plugin is developed using the SNAP Standalone Tool Adapter (STA) interface. The STA plugin forms a thin interface between SNAP and a self-contained Python environment that holds the Sen-ET code and all the Python dependencies required to execute it. The STA plugin can be downloaded from the Sen-ET website (`http://esa-sen4et.org/outputs/software/`) and will automatically download the Python environment on first run. The Python bundle is also available for manual download at (`https://senetfiles.blob.core.windows.net/files/sen-et-conda-Linux64.run`, respectively `https://senetfiles.blob.core.windows.net/files/sen-et-conda-Win64.exe`).

The STA plugin downloaded from `http://esa-sen4et.org/outputs/software/` is a ZIP archive which includes one `.nmb` file for each Sen-ET plugin operator. To install it, launch SNAP and in the main menu select *Tools > Plugins*. This will open the Plugins dialog on which go to the *Downloaded* tab and click the *Add Plugins...* button (Figure 3.1).

Before proceeding with the installation, it is advised to update SNAP to last available version. Additionally, SNAP should be configured for use with **Python 3.6**. More details on how to configure SNAP for use with Python, can be found at "Configure SNAP for use with Python".
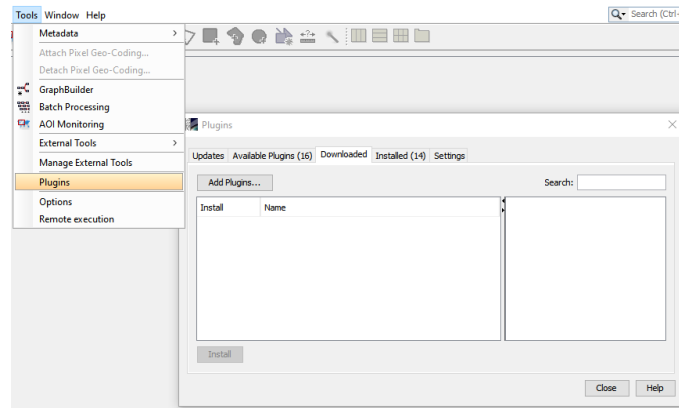

Figure 3.1: SNAP Plugins dialog

In the *Add Plugins* dialog, navigate to the directory to which the STA was downloaded and select all the `.nbm` files in this directory. All the plugin operators should now be listed in the *Plugins* dialog and the tick box next to each operator should be ticked. Clicking on *Install* will install all the operators (Figure 3.2).
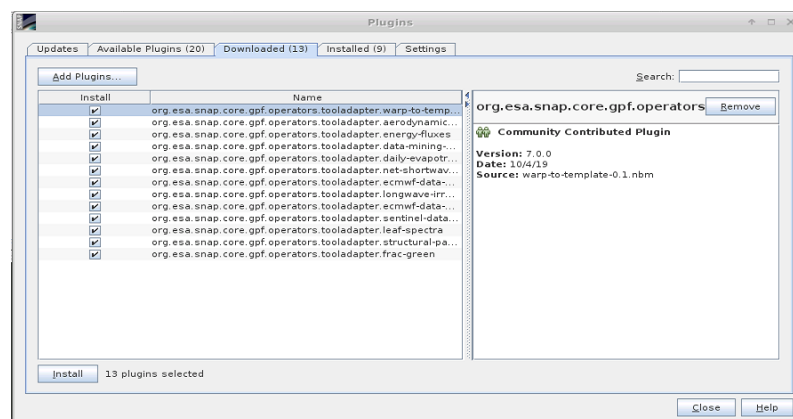

Figure 3.2: Selecting operators to install

If the operators are successfully installed they should appear in the SNAP main menu under *Optical > Thematic Land Processing > SEN-ET*. In total there should be 13 operators 3.3. If some were not installed properly then please consult the Troubleshooting section of this manual (Section 3.4).
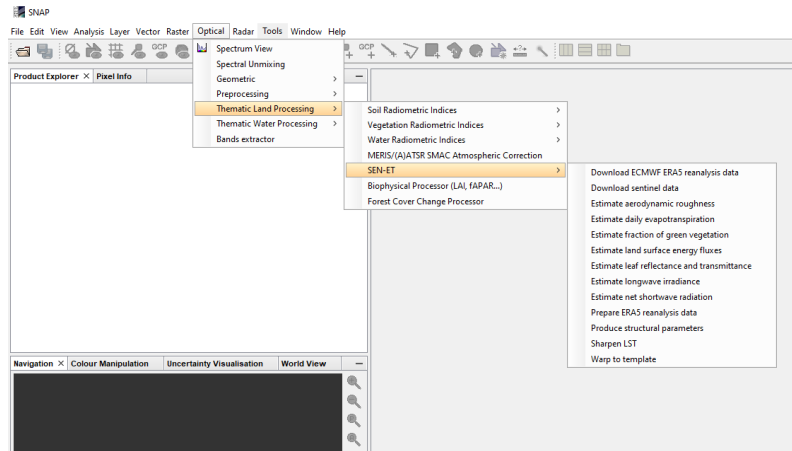
Figure 3.3: Installed Sen-ET operators.

The first time any of the Sen-ET operators is run the user will receive a *SNAP - Warning* message about path not existing. After clicking *OK* another dialog will appear asking user if they want to proceed with bundle download/installation (Figure 3.4). After clicking "Yes" the download and installation of the plugin bundle (the self-contained Python environment) will happen automatically. When the bundle installation finishes, a message will notify of the successful installation of the bundle. The Sen-ET SNAP plugin is installed and ready for use.
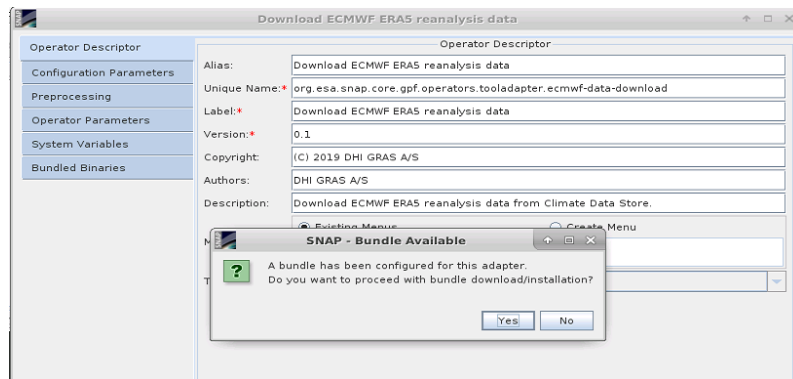

Figure 3.4: Bundle download/installation

3.3 User interfaces

The Sen-ET plugin consist of thirteen operators and four SNAP graphs. The operators contain new functionality developed as part of the Sen-ET project while the graphs using existing SNAP functionality to perform some pre-processing tasks for Sentinel-2 and Sentinel-3 data. After completing the installation the Python code for the new operators can be found in ~/.snap/auxdata/sen-et-conda-<OS>64/sen-et-snap-scripts directory where ~ is

the user directory and <OS> can be *Linux* or *Windows* depending on the operating system used. The four graphs are located in ~/.snap/auxdata/sen-et-conda-<OS>64/sen-et-snap-scripts/auxdata/graphs.

The operators have three user interfaces: graphical user interface (GUI) through SNAP GUI, command line interface through SNAP Graph Processing Tool and a command line interface through Python.

3.3.1 SNAP graphical user interface

For the GUI the user needs to launch SNAP and select the operators from the main menu under *Optical > Thematic Land Processing > SEN-ET* (Figure 3.3). Graphs can be run from within SNAP by going to *Tools > Graph Builder* in the main menu and then selection *File > Load Graph* in the Graph Builder dialog. In theory it is possible to set graph inputs and outputs in the Graph Builder. In practice, it is recommended to make a copy of the graph XML file, insert the inputs and outputs in the copy and then load the fully prepared graph in the Graph Builder to execute it. Within the graph xml file the inputs and output values which need to be modified are starting and ending with an exclamation mark (!) , e.g.: <file>!INPUT_Sentinel-2_L2A!</file>.

The inputs, outputs and parameters of the operators and graphs are described in the sections below. The operators and graphs are described in the order in which they should be run as shown in Figures 2.1-2.4.

3.3.1.1 Download Sentinel data

This operator searches and downloads L2A Sentinel-2 and Sentinel-3 images from Copernicus Open Access Hub, given an area of interest (AOI) and a date range. The images will be downloaded to the folder containing the target product.

Inputs
None
Parameters

- Geojson file with AOI - geojson file with geographic projection holding the extents of Area of Interest (AOI) in which to search for Sentinel scenes

- Start date for image search (YYYYMMDD) - beginning of date range in which to search for Sentinel scenes

- End date for image search (YYYYMMDD) - end of date range in which to search for Sentinel scenes

- Satellite platform - Sentinel-2 or Sentinel-3

- Directory to which download products - local directory in which downloaded scenes will be saved

- Copernicus Open Access Hub username - username of the account which will be used to download the data

- Copernicus Open Access Hub password - password of the account which will be used to download the data

- Download images - whether the images should be downloaded or just searched for and search results saved in a text file in the download directory

- Maximum cloud cover percentage for S2 images - download only Sentinel-2 scenes with cloud cover below this threshold

- Limit to Sentinel-2 tiles - download only Sentinel-2 scenes which have specified tile in the filename

Output
None

3.3.1.2 Sentinel-2 preprocessing graph

This graph re-samples the downloaded L2A Sentinel-2 scene to 20 m, subsets required bands and saves them as individual products and estimates biophysical parameters from the reflectance bands.

Inputs

- !INPUT_Sentinel-2_L2A! - Sentinel-2 scene downloaded by *Download Sentinel data* operator

Parameters
None
Outputs

- !OUTPUT_reflectance! - product containing the 20 m reflectance bands (B2, B3, B4, B5, B6, B7, B8A, B11, B12)

- !OUTPUT_sun_zenith_angle! - product containing the scene's sun zenith angle band (sun_zenith)

- !OUTPUT_mask! - product containing cloud mask derived from scene's quality flags

- !OUTPUT_biophysical! - product containing biophysical parameters (LAI, FAPAR, Fcover, Cab, Cw)

3.3.1.3 Add elevation graph

This graph creates a high resolution digital elevation model (DEM) for the given L2A Sentinel-2 scene

Inputs

- !INPUT_Sentinel-2_Mask! - Sentinel-2 mask product produced by *Sentinel-2 preprocessing* graph

Parameters
None
Outputs

- !OUTPUT_SRTM_elevation! - High resolution DEM product

3.3.1.4   Add landcover graph

This graph creates A land-cover map for the given Sentinel-2 scene using the ESA CCI Land Cover 2015 map

Inputs

- !INPUT_Sentinel-2_Mask! - Sentinel-2 mask product produced by *Sentinel-2 preprocessing* graph

Parameters
None
Outputs

- !OUTPUT_CCI_landcover! - CCI land-cover product

3.3.1.5   Estimate leaf reflectance and transmittance

This operator estimates leaf reflectance and transmittance based on plant chlorophyl and water content.

Inputs

- Plant biophysical properties product - output of *Sentinel-2 preprocessing* graph

Parameters
None
Output

- Output image - Product containing the leaf reflectance and transmittance parameters

3.3.1.6   Estimate fraction of green vegetation

This operator estimates the fraction of vegetation which is green based on the leaf area index (LAI), fraction of absorbed photosynthetically active radiation (FAPAR) and sun zenith angle bands.

Inputs

- Sentinel-2 sun zenith angle product - output of *Sentinel-2 preprocessing* graph

- Plant biophysical properties product - output of *Sentinel-2 preprocessing* graph

Parameters

- Minimum fraction of vegetation which is green

Output

- Output image - Product containing the fraction of green vegetation data

3.3.1.7 Produce maps of vegetation structural parameters

This operator produces maps of vegetation structural parameters required for TSEB model runs, based on a land cover map and a look-up table.

Inputs

- Land-cover product - output of *Add landcover* graph

- Plant biophysical properties product - output of *Sentinel-2 preprocessing* graph

- Fraction of green vegetation product - output of *Estimate fraction of green vegetation* operator

Parameters

- Land-cover band - Name of land-cover band as produced by the *Add landcover* graph

- Look-up table - File containing the look-up table (default location: ∼/`.snap/auxdata/sen-et-co` directory where ∼ is the user directory and <OS> can be *Linux* or *Windows* depending on the operating system used)

- Produce vegetation height maps - indicate if the vegetation height maps should be produced

- Produce vegetation fractional cover maps - indicate if the vegetation fractional cover maps should be produced

- Produce canopy height to width ratio maps - idicate if the canopy to width ratio maps should be produced

- Produce leaf width maps - indicate if the leaf width maps should be produced

- Produce leaf inclination distribution maps - indicate if the leaf inclination distribution maps should be produced

- Produce landcover map with IGBP classes - indicate if the landcover map with IGBP classes should be produced

Output

- Output image - Product containing the maps of vegetation structural parameters

3.3.1.8 Estimate aerodynamic roughness

This operator estimates aerodynamic roughness length for momentum transport (m) and zero-plane displacement height (m) based on the leaf area index (LAI) and the maps of vegetation structural parameters.

Inputs

- Plant biophysical properties product - output of *Sentinel-2 pre-processing* graph

- Vegetation structural parameters product - output of *Produce maps of vegetation structural parameters* operator

Parameters

- Soil roughness

Output

- Output image - Product containing the aerodynamic roughness length for momentum transport and zero-plane displacement height.

3.3.1.9   Sentinel-3 pre-processing graph

This graph reprojects the downloaded L2A Sentinel-3 scene to the given AOIm subsets required bands and saves them as individual products.

Inputs

- !INPUT_Sentinel-3_L2A! - Sentinel-3 scene downloaded by *Download Sentinel data* operator

Parameters

- !INPUT_AOI_WKT! - Area of interest formatted as well-known text (WKT)

Outputs

- !OUTPUT_observation_geometry! - product containing the scene's sat_zenith_tn, solar_zenith_tn, longitude_tx, latitude_tx bands

- !OUTPUT_mask! - product containing cloud mask derived from scene's quality flags

- !OUTPUT_LST! - product containing land surface temperature data

3.3.1.10   Warp to template

This operator reprojects, resamples and subsets a source image to a template image using GDAL Warp.

Inputs

- Source image

- Template image

Parameters

- Resample algorithm - choose one of the available resample algorithms

Output

- Output image - The source image after reprojection, resampling and subsetting.

3.3.1.11 Sharpen LST

This operators calls the Python implementation of the Data Mining Sharpener. It can be used to sharpen SLSTR Land Surface Temperature to Sentinel-2 spatial resolution.
Inputs

- Sentinel-2 reflectance product - output of *Sentinel-2 preprocessing* graph

- Sentinel-3 LST product - output of *Sentinel-3 preprocessing* graph

- High resolution DEM - output of *Add elevation* graph

- High resolution Sentinel-3 geometry product - output of *Warp to template* operator

- LST quality mask product - output of *Sentinel-3 preprocessing* graph

Parameters

- Date and time(UTC) of Sentinel-3 acquisition (YYYY-MM-DD HH:MM)

- Elevation band - Name of the elevation band

- Good quality mask values

- Homogeneity inclusion threshold

- Moving window size

- Parallel jobs

Output

- Output image - Product containing the sharpened Land Surface Temperature band

3.3.1.12 Download ECMWF ERA5 reanalysis data

This operators downloads ECMWF ERA5 reanalysis data from the Climate Data Store (CDS). Note that this requires CDS registration and the CDS key located in the right directory (see `https://cds.climate.copernicus.eu/api-how-to`). The CDS API client is already included in the Sen-ET Python package and does not need to be installed separately.
Inputs
None
Parameters

- Area of interest (N/W/S/E) - Coordinates of AOI in decimal degrees

- Start date for data download(YYYY-MM-DD)

- End date for data download(YYYY-MM-DD)

- Download air temperature data - indicate if air temperature data should be downloaded

- Download air humidity data - indicate if air humidity data should be downloaded

- Download pressure data - indicate if pressure data should be downloaded

- Download wind data data - indicate if wind data data should be downloaded

- Download clear-sky incoming solar radiation data - indicate if clear-sky incoming solar radiation data should be downloaded

- Download downward solar radiation data - indicate if downward solar radiation data should be downloaded

- Overwrite file if it exists - indicate if the the file should be overwritten if the file already exists

Output

- File to which download data (NetCDF) - Product containing the ECMWF ERA5 reanalysis data

3.3.1.13 Prepare ERA5 reanalysis data

This operator prepares ERA5 reanalysis surface meteorological data based on the ECMWF ERA5 reanalysis data and the high resolution DEM.

Inputs

- High resolution DEM - output of *Add elevation* graph

Parameters

- Elevation band - name of the elevation band

- File to which ECMWF data was downloaded (NetCDF)

- Date and time (UTC) for which to prepare meteorological data (YYYY-MM-DD HH:MM)

- Time zone of the center of area of interest

- Prepare air temperature data - indicate if air temperature data should be prepared

- Prepare vapour pressure data - indicate if vapour pressure data should be prepared

- Prepare air pressure data - indicate if air pressure data should be prepared

- Prepare wind speed data - indicate if wind speed data should be prepared

- Prepare clear-sky incoming solar radiation data - indicate if clear-sky incoming solar radiation data should be prepared

- Prepare average daily solar irradiance data - indicate if average daily solar irradiance data should be prepared

Output

- Output image - Product containing the ERA5 reanalysis surface meteorological data

3.3.1.14   Estimate longwave irradiance

This operator estimates atmosphere longwave irradiance (W/m^2) based on meteorological inputs.

Inputs

- Meteorological inputs product - output of *Prepare ERA5 reanalysis data* operator

Parameters

- Air temperature band (K) - name of the air temperature band

- Vapour pressure band (mb) - name of the vapour pressure band

- Air pressure band (mb) - name of the air pressure band

- Air temperature measurement height (m)

Output

- Output image - Product containing the atmosphere longwave irradiance data

3.3.1.15   Estimate net shortwave radiation

This operator estimates net shortwave radiation based on meteorological and biophysical inputs.

Inputs

- Leaf spectral properties product - output of *Estimate leaf reflectance and transmittance* operator

- Plant biophysical properties product - output of *Sentinel-2 pre-processing* graph

- Vegetation structural parameters product - output of *Produce maps of vegetation structural parameters* operator

- Meteorological inputs product - output of *Prepare ERA5 reanalysis data* operator

- Sun zenith angle product - Sentinel-3 observation geometry product after being put through *Warp to template* operator

Parameters

- Visible soil reflectance

- Near-infrared soil reflectance

Output

- Output image - Product containing the net shortwave radiation data

3.3.1.16   Estimate land surface energy fluxes

This operator estimates land surface energy fluxes (latent, sensible, ground heat and net radiation) using One-Source Energy Balance model for bare soil pixels and Two-Source Energy Balance model for vegetated pixels.

Inputs

- Sharpened land surface temperature product - output of *Sharpen LST* operator

- LST view zenith angle product - output of *Sentinel-3 pre-processing* graph

- Plant biophysical properties product - output of *Sentinel-2 pre-processing* graph

- Vegetation structural parameters product - output of *Produce maps of vegetation structural parameters* operator

- Fraction of green vegetation product - output of *Estimate fraction of green vegetation* product

- Aerodynamic roughness product - output of *Estimate aerodynamic roughness* operator

- Meteorological inputs product - output of *Prepare ERA5 reanalysis data* operator

- Net shortwave radiation product - output of *Estimate net shortwave radiation* operator

- Longwave irradiance product - output of *Estimate longwave irradiance* operator

- Sentinel-2 mask product - output of *Sentinel-2 pre-processing* graph

Parameters

- Soil roughness

- Alpha pt

- Atmospheric measurement height

- Green vegetation emissivity

- Soil emissivity

- Save component fluxes - indicate if component fluxes data should be saved

- Save component temperature - indicate if component temperature data should be saved

- Save aerodynamic parameters - indicate if aerodynamic parameters data should be saved

Output

- Output image - Product containing the land surface energy fluxes

3.3.1.17 Estimate daily evapotranspiration

This operator estimates daily evapotranspiration by extrapolating instantaneous latent heat flux using daily solar irradiance.

Inputs

- Instantaneous energy fluxes product - output of *Estimate land surface energy fluxes* operator

- Meteorological inputs product - output of *Prepare ERA5 reanalysis data* operator.

Parameters
None

Outputs

- Output image - Product containing evapotranspiration in mm/day

3.3.2 Command line interfaces

There are two command line interfaces: SNAP Graph Processing Tool and Python. Through the use of those interfaces it is possible for advanced users to automate the production of actual evapotranspiration maps. This can be achieved by chaining the command line calls in a shell script, Python script or any other script or program.

3.3.2.1 SNAP Graph Processing Tool

The easiest way to access Graph Processing Tool (GPT) is to launch the `SNAP Command-Line` application, which is installed together with SNAP. Afterwards, it is enough to type `gpt` in the command line application. Alternatively, Windows command prompt or Linux shell can be used but then full path to GPT needs to be specified (e.g. on Windows the default path is `C:/Program Files/snap/bin/gpt`).

Calling `gpt` or `gpt -h` will display the GPT options as well as all the operators available in GPT, including the Sen-ET operators. The Sen-ET operators are named the same as the subsections of section 3.3.1, which also describes the purpose, inputs, outputs and parameters of each operator.

Calling `gpt <operator_name> -h` will display the information about the specified operator. In case of Sen-ET operators, the name should enclosed in quotation marks, since the names contain spaces (e.g. see Fig. 3.5). To execute and operator, either all the parameters, inputs and outputs can be specified directly on the command line or an XML graph can be created and then passed to GPT. The former method is preferred with Sen-ET operators since it is more robust. In both cases the names of parameters, inputs and outputs are displayed with the `-h` option.

An example command to produce aerodynamic roughness maps is shown below and in Fig. 3.6:

```
gpt "Estimate aerodynamic roughness"
"-SPlant biophysical properties product=C:\test\sen-et\gpf\output_biophys.dim"
"-SVegetation structural parameters product=C:\test\sen-et\gpf\output_struct_params.di
-Psoil_roughness=0.01
-PtargetProductFile=C:\test\sen-et\gpf\aerodynamic_roughness.dim
```

Figure 3.5: An example of using GPT to get Sen-ET operator help.

```
-t C:\test\sen-et\gpf\aerodynamic_roughness.dim
```
Note that parameters which contain spaces are enclosed in quotes and that the same output file is specified for `-PtargetProductFile` and `-t` parameters. The second parameter is optional, however an error will be displayed if it is omitted even though the operator will execute successfully and output file will be created.

Figure 3.6: An example of using GPT to execute Sen-ET operator.

3.3.2.2 Python interface

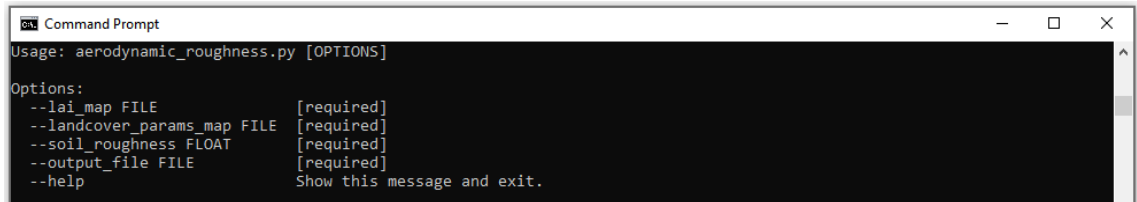An alternative to GPT is to use the direct command line interface of each operator's Python implementation. For this the user needs to use Windows command prompt or Linux shell, go to the Python code directory (∼/`.snap/auxdata/sen-et-conda-<OS>64/sen-et-snap-scripts`) and type
```
../python <operators_name>.py
```
where `<operators_name>` needs to be replaced by the name of the operator script to be run.

The `-help` option should be used to display a list of parameters used by an operator (e.g. `../python aerodynamic_roughness.py -help` - see Fig. 3.7 for output). An example command to produce aerodynamic roughness maps is shown below:

```
../python aerodynamic_roughness.py -lai_map C:\test\sen-et\gpf\output_biophys.dim
-landcover_params_map C:\test\sen-et\gpf\output_struct_params.dim -soil_roughness
0.01 -output_file C:\test\sen-et\gpf\aerodynamic_roughness.dim
```


Figure 3.7: An example of using Python command line interface to get Sen-ET operator help

Note that SNAP installation is still required when using the Python command line interface since snappy (SNAP Python module) is used in the scripts to read input images and to write output images.

3.4 Troubleshooting

3.4.1 Some operators are not visible

After the installation of the Sen-ET plugin, as described in section 3.2, it is possible that some of the operators are not visible. To solve this issue, the user will have to restart SNAP application. If this does not solve the issue, the user will have to navigate to *Tools > Plugins > Installed* , select all the installed Sen-ET operators, press the Uninstall button and re-do the installation steps 3.2.

3.4.2 Bundle installation never terminates (on Windows)

On Windows, sometimes the bundle installation starts, the progress bar goes to 100%, but the installation never terminates. In fact the installation did succeed in this case. So after restarting the SNAP application, the Sen-ET operators are ready to use.

3.4.3 SNAP subset operator does not subset bands

The Sentinel-2 and Sentinel-3 pre-processing graphs take a subset of the source product's bands using SNAP's `Subset` operator, in order to produce more compact sub-products. Sometimes, the bands are not actually removed and the output files contain all the available bands of the source product. When this happens is semi-random (SNAP-style). This is not a crucial error, but it will cause much higher memory consumption for some of the Sen-ET operators that make use of those sub-products because unneeded bands are loaded.

If the users want to create the compact sub-products before using them as input to the Sen-ET operators, they can use the SNAP *GraphBuilder* to make a simple graph consisting of only three connected operators: Read, Subset and Write, and by selecting a sub-product

as source product in the read operator and the subset of bands in the subset operator, the new compact sub-products will be generated with the name specified as target product in the write operator.

3.4.4   Import error - snappy / jpy

If during the execution of the Sen-ET operators, the user experiences an import error for either snappy or jpy, it means that SNAP was not configured properly for use with SNAP. In order to fix this issue, the user will have to re-install SNAP and configure SNAP for use with Python. The Python version has to be *3.6* in order to match with the Conda environment that we distribute.

3.5   Code availability

The source code of all the plugin components is available directly in their respective GitHub repositories:

- `https://github.com/DHI-GRAS/senEtSnapSta` - SNAP STA configuration files for each operator

- `https://github.com/DHI-GRAS/sen-et-snap-scripts` - Python scripts for each operator used to to prepare data and execute energy flux model

- `https://github.com/DHI-GRAS/pyTSEB/tree/optimize` - optimised version of the Python implementation of the Two-Source Energy Balance model used in the plugin

- `https://github.com/radosuav/pyDMS` - Python implementation of the Data Mining Sharpener used to sharpened SLSTR LST data

Chapter 4

Theoretical basis

This sections explains the theoretical basis behind the thermal sharpening approach, based on Data Mining Sharpener (DMS), and the land-surface energy flux model, based on Two-Source Energy Balance (TSEB) model. It is mainly an extract from a two journal articles: Guzinski and Nieto [2] and Guzinski et al. [1]. For more details the users are referred to those articles and to their references.

4.1   Thermal sharpening

The thermal data sharpening approach is based on ensemble of modified decision trees, with the basic scheme (Fig. 4.1), including data preparation and bias-reduction modules based on Gao et al. [3]. The full source code of the Python implementation used in this plugin is available online (`https://github.com/radosuav/pyDMS`). Each S3 scene is matched with an S2 scene acquired at most ten days before or after the S3 acquisition and the regression model used for sharpening is derived specifically for each scene pair.

Briefly, the atmospherically corrected Sentinel-2 optical data with a spatial resolution of 20 m is resampled to match the pixel sampling of the SLSTR sensor (around 1 km spatial resolution). Concurrently, the SRTM DEM is used to derive slope and aspect maps which, together with S3 overpass time, are used to estimate the solar irradiance incident angle of a flat tilted surface. The DEM and the solar angle maps are also resampled to the SLSTR resolution. A multivariate regression model is then trained with the three resampled datasets used as predictors and the T_{rad} used as the dependent variable. The selection of training samples is performed automatically by estimating the coefficient of variation (CV) of all the high-resolution pixels falling within one low-resolution pixel and selecting 80% of pixels with lowest CV. The regression model is based on bagging ensemble [4] of decision trees. The decision trees are additionally modified such that all samples within a regression tree leaf node are fitted with a multivariate linear model, as proposed by [3].

The regression models are trained on the whole S2 tile (100 km by 100 km) as well as on subsets of 30 by 30 S3 pixels in a moving window fashion. Once they are trained they are also applied on the whole scene and on each window. The bias between the predicted high-resolution T_{rad} pixels aggregated to the low-resolution and the original low-resolution T_{rad} is calculated and the outputs of the whole-scene and moving-window regressions are combined based on a weight inversely proportional to the bias [3]. Finally,
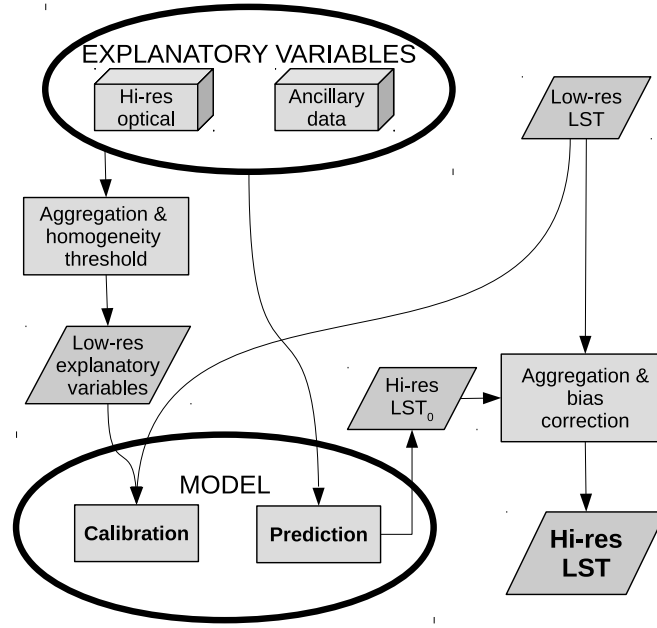
Figure 4.1: General thermal sharpening workflow. Explanatory variables include both multispectral band as well any other ancillary explanatory variable, such as elevation, land cover type or exposure. Model could be any regression model, such as multivariate linear regression or machine learning techniques

the T_{rad} predicted by the regression model is corrected by comparing the emitted longwave radiance of the sharpened fine T_{rad} versus the original coarse T_{rad}. A bias-corrected T_{rad} is therefore re-calculated by adding an offset all fine scale pixels falling within coarse scale pixel in order to remove any residual bias. This is done to ensure the conservation of energy between the two thermal images with different spatial resolutions [3]. The output of the sharpening is a 20 m representation of the LST.

4.2 Land-surface energy flux modelling

The land surface fluxes' modelling scheme is based on the Two-Source Energy Balance (TSEB) modelling scheme proposed by [5] and further evolved in [6] and subsequent publications. The full source code of the Python implementation of the model used in this plugin is available online (`https://github.com/DHI-GRAS/pyTSEB/tree/optimize`). The model is briefly described below.

In the TSEB modelling scheme the directional radiometric land surface temperature ($T_R(\theta)$) observed from satellite is split into its component temperatures, of canopy (T_C) and soil (T_S):

$$T_R(\theta) \approx [f(\theta)T_C^4 + (1 - f(\theta))T_S^4]^{0.25} \qquad (4.1)$$

$f(\theta)$ is fraction of the field of view of the sensor occupied by vegetation at a view zenith angle θ:

$$f(\theta) = 1.0 - \exp(-K_{be}\Omega_\theta F) \qquad (4.2)$$

where K_{be} is the extinction coefficient estimated according to [7] and taking leaf angle distribution into account, Ω_θ is the angular clumping factor estimated using equation from [6] and F is the plant area index. In this study $f(\theta)$ has an imposed maximum limit of 0.9 in order to avoid the model becoming unstable at very high values of F and θ. The two component temperatures, together with air temperature (T_A), are then used to calculate the canopy and soil sensible heat fluxes (H_C and H_S respectively):

$$H = H_C + H_S \tag{4.3}$$

$$H_C = \rho c_p \frac{T_C - T_{AC}}{R_x} \tag{4.4}$$

$$H_S = \rho c_p \frac{T_S - T_{AC}}{R_S} \tag{4.5}$$

$$\tag{4.6}$$

where T_{AC} is the intra-canopy air temperature:

$$T_{AC} = \frac{\frac{T_A}{R_A} + \frac{T_S}{R_S} + \frac{T_C}{R_x}}{\frac{1}{R_A} + \frac{1}{R_S} + \frac{1}{R_x}} \tag{4.7}$$

and R_A, R_S and R_x are aerodynamic resistances to heat transport in the surface air layer, soil surface and boundary layer of leaf canopy respectively. Latent heat fluxes from canopy (LE_C) and soil (LE_S) are also computed separately with LE_C initially estimated using the Priestley-Taylor approximation and assumption of potential transpiration and LE_S estimated as a residual of the other soil fluxes:

$$LE = LE_C + LE_S \tag{4.8}$$

$$LE_C = R_{n,C}\alpha_{PT}f_g\frac{sp}{sp + \gamma} \tag{4.9}$$

$$LE_S = R_{n,S} - G - H_S \tag{4.10}$$

where α_{PT} is the Priestley-Taylor parameter, f_g is the fraction of vegetation that is green and transpiring, sp is the slope of the water vapour saturation pressure curve and γ is the psychometric constant. $R_{n,C}$ and $R_{n,S}$ are the net radiation of canopy and soil respectively composed of short-wave component calculated using the approach of [7] and long-wave component estimated using the approach of [6]. The ground heat flux (G) is derived as a constant fraction of soil net radiation. In case LE_S is estimated as being negative (very unlikely state during sunny conditions), α_{PT} is reduced under the assumption that LE_C was overestimated and the calculations are repeated.

4.3 Limitations

The approach to sharpen low-resolution LST with high-resolution optical data is based on the assumption that there exists a statistical relation between the two dataset. The sharpening methodology used in this plugin permits this relation to be non-linear and even very complex but it still must exist. While there is no general, globally transferable relation between TIR and optical data, it is possible to derive it when the two datasets are limited in space and time. This study shows that in such localised cases it is possible

to use the sharpened LST to derive the land surface fluxes at high spatial resolution with acceptable accuracy. However, even then the range of high-resolution fluxes will not be as large as it would be if high-resolution LST observations were used, due to the aggregating effect present in the low-resolution observations.

Another inherent limitation of estimating ET using DMS sharpened LST is the underlying assumption that the TIR and optical datasets contain the same or related information about the modelled physical phenomena. In practice they might contain complementary information. For example, crop water stress can be observed in the TIR domain some weeks before it becomes visible in the optical domain but both types of observations are required to map the water stress in different stages of the crop phenological cycle [8]. On the other hand, Sentinel-2 bands in the shortwave infrared (SWIR) part of the electromagnetic spectrum do contain information about vegetation water content [9] and (under certain assumptions) about soil water content [10]. Therefore, more research is required to determine whether the DMS sharpened LST is suitable for applications such as early detection of vegetation water stress and precision irrigation, in which crops are subject to certain stress without provoking a decrease in yield/biomass. In other applications, such as in regional field-scale water use mapping (e.g. [11]) the use of sharpened LST as input to ET models should produce acceptable results.
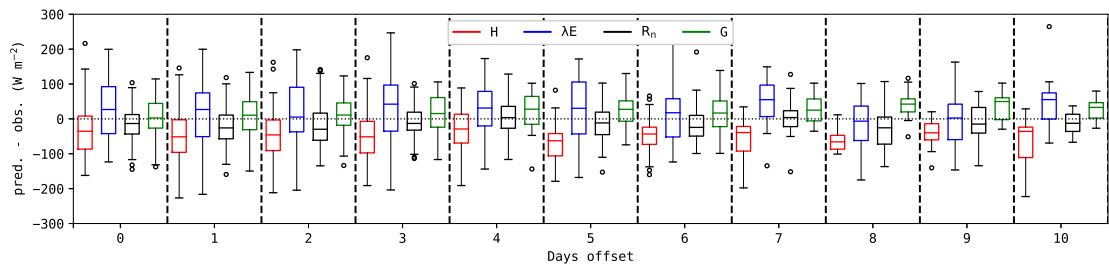

Figure 4.2: Error (modelled - measured) distribution of fluxes modelled with TSEB-PT model using sharpened T_{rad} depending on offset days between a Sentinel-3 T_{rad} image and the fine-scale Sentinel-2 multispectral image. Error computed for all validation sites together.

Finally, the sharpening of a coarse resolution T_{rad} image using fine resolution images acquired on different days, with a maximum of 10 days offset, might lead to additional uncertainties. This is caused by the fact that some changes in either land cover properties, (e.g. vegetation growth, harvests, fires) or moisture conditions (e.g. rainfall or irrigation) might happen between the Sentinel 2 and 3 acquisitions. Fig. 4.2 shows that at a general level (all validation sites taken together) this does not appear to be a significant issue as the error does not increase as the day offset between thermal and optical acquisitions gets larger. Particularly relevant in this analysis is H since it is the energy component that is directly related to T_{rad}, and hence more prone to errors in sharpening. However, more studies should be conducted to look at the effect of the day offset in particular situations, e.g. in crops during senescence or with localized irrigation patterns.

Bibliography

[1] Radoslaw Guzinski, Hector Nieto, Inge Sandholt, and Georgios Karamitilios. High resolution evapotranspiration using sentinel-2 and -3 satellites: Evaluation of metric, tseb and esvep models with thermal sharpening methods. *Hydrology and Earth System Sciences*, Submitted.

[2] Radoslaw Guzinski and Héctor Nieto. Evaluating the feasibility of using Sentinel-2 and Sentinel-3 satellites for high-resolution evapotranspiration estimations. *Remote Sensing of Environment*, 221:157–172, February 2019. ISSN 0034-4257.

[3] Feng Gao, William P. Kustas, and Martha C. Anderson. A Data Mining approach for Sharpening thermal satellite imagery over land. *Remote Sensing*, 4(11):3287–3319, 2012.

[4] Leo Breiman. Bagging predictors. *Machine Learning*, 24(2):123–140, 1996.

[5] J. M. Norman, W. P. Kustas, and K. S. Humes. Source approach for estimating soil and vegetation energy fluxes in observations of directional radiometric surface temperature. *Agricultural and Forest Meteorology*, 77(3-4):263–293, 1995.

[6] William P Kustas and John M Norman. Evaluation of soil and vegetation heat flux predictions using a simple two-source model with radiometric temperatures for partial canopy cover. *Agricultural and Forest Meteorology*, 94(1):13–29, 1999.

[7] G.S. Campbell and J.M. Norman. *An Introduction to Environmental Biophysics*. Springer-Verlag New York, New York, 2nd edition edition, 1998.

[8] H. Hoffmann, R. Jensen, A. Thomsen, H. Nieto, J. Rasmussen, and T. Friborg. Crop water stress maps for an entire growing season from visible and thermal UAV imagery. *Biogeosciences*, 13(24):6545–6563, December 2016. ISSN 1726-4189. doi: 10.5194/ bg-13-6545-2016. URL http://www.biogeosciences.net/13/6545/2016/.

[9] Pietro Ceccato, Stéphane Flasse, Stefano Tarantola, Stéphane Jacquemoud, and Jean-Marie Grégoire. Detecting vegetation leaf water content using reflectance in the optical domain. *Remote Sensing of Environment*, 77(1):22–33, July 2001. ISSN 0034-4257. doi: 10.1016/S0034-4257(01)00191-2. URL http://www.sciencedirect. com/science/article/pii/S0034425701001912.

[10] Morteza Sadeghi, Ebrahim Babaeian, Markus Tuller, and Scott B. Jones. The optical trapezoid model: A novel approach to remote sensing of soil moisture applied to Sentinel-2 and Landsat-8 observations. *Remote Sensing of Environment*, 198:52–68,

September 2017. ISSN 0034-4257. doi: 10.1016/j.rse.2017.05.041. URL http://www.sciencedirect.com/science/article/pii/S0034425717302493.

[11] Gabriel B. Senay, MacKenzie Friedrichs, Ramesh K. Singh, and Naga Manohar Velpuri. Evaluating Landsat 8 evapotranspiration for water use mapping in the Colorado River Basin. *Remote Sensing of Environment*, 185:171–185, November 2016. ISSN 0034-4257. doi: 10.1016/j.rse.2015.12.043. URL http://www.sciencedirect.com/science/article/pii/S0034425715302650.