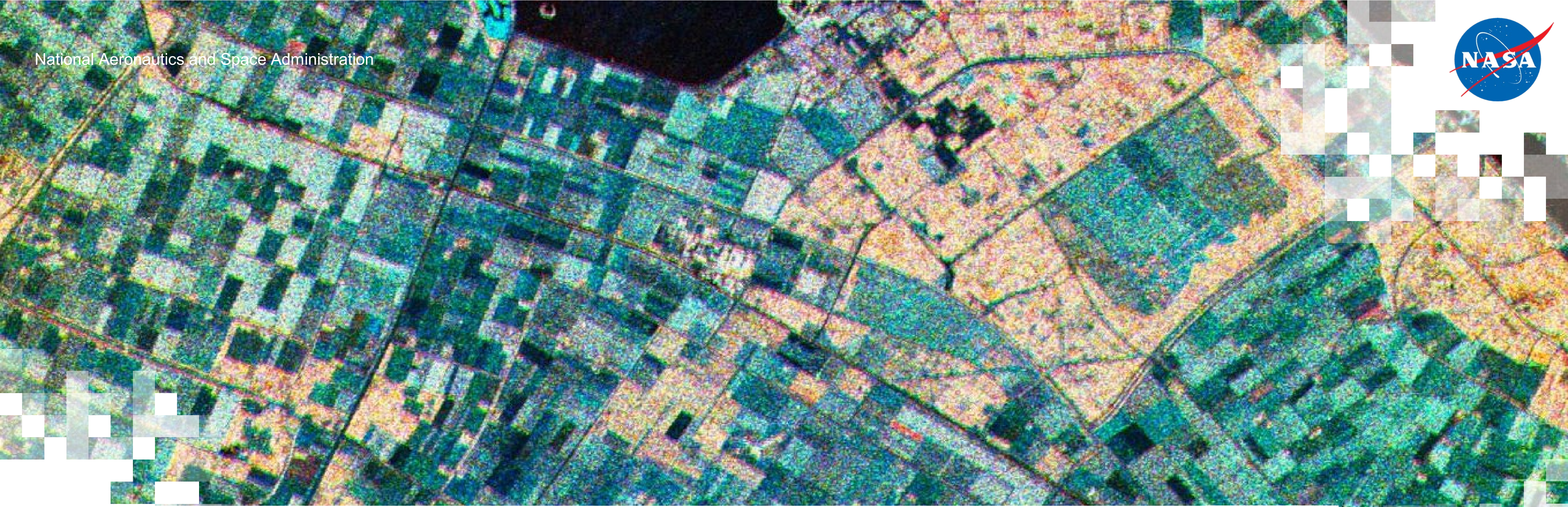

National Aeronautics and Space Administration

Agriculture and Agri-Food Canada

Agriculture et Agroalimentaire Canada

University of Ljubljana

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esa

Crop Mapping using Synthetic Aperture Radar (SAR) and Optical Remote Sensing

April 11, 2023

Training Outline

April 4, 2023

Crop Classification with Time Series of Polarimetric SAR Data

April 6, 2023

Crop Classification with Time Series Optical and Radar Data

April 11, 2023

Monitoring Crop Growth Through SAR-Derived Crop Structural Parameters

Homework and Certificate

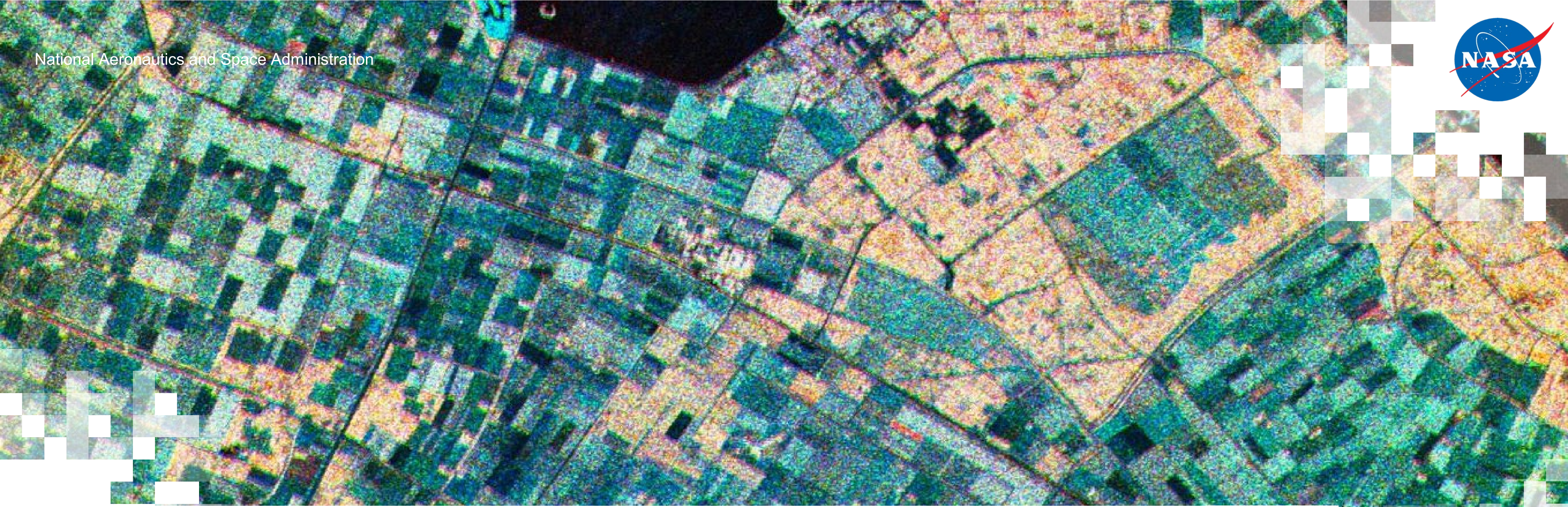
- Homework Assignment:
  - Answers must be submitted via Google Form
  - Due Date: April 25, 2023
- A certificate of completion will be awarded to those who:
  - Attend all live webinars
  - Complete the homework assignment by the deadline (access from website)
  - You will receive a certificate approximately two months after the completion of the course from: marines.martins@ssaihq.com

Training Objectives

After participating in this 3-part training, attendees will be able to:

- Explain how polarimetric parameters are used for crop condition assessment
- Demonstrate how to perform Sentinel-1 SAR preprocessing to derive quasi polarimetric parameters
- Perform a calibration of a SAR-based vegetation index to NDVI
- Monitor crop growth with multitemporal polarimetric SAR (PolSAR) data from Sentinel-1
- Examine crop growth using a canopy structure dynamic model and time series of Sentinel-1 imagery
- Classify crop type using a time series of radar and optical imagery (Sentinel-1 & Sentinel-2)

National Aeronautics and Space Administration



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Monitoring Crop Growth Through SAR-Derived Structural Parameters

Emily Lindsay, Heather McNairn, and Xianfeng Jiao – Agriculture and Agri-Food Canada

April 11, 2023

APPLIED REMOTE SENSING TRAINING PROGRAM

TRAIN - EMPOWER - ADVANCE

Outline

Introduction (Heather McNairn)

- Rationale for developing a SAR Vegetation Index (SAR VI)
- Sentinel-1 SAR parameters for crop condition monitoring
- SAR VI calibration to Normalized Difference Vegetation Index (NDVI)
- Crop Structure Dynamics Model

Hands on exercise (Emily Lindsay)

- Sentinel-1 SAR preprocessing
- Deriving quasi-polarimetric parameters from Sentinel-1 Single Look Complex (SLC) data
- Calibration of SAR VI to NDVI

Learning Objectives

After participating in this training, attendees will be able to:

- State the benefits of incorporating radar data with optical imagery for operational crop condition assessment monitoring.
- Explain how polarimetric parameters are used for crop condition assessment.
- Summarize the workflow for creating a SAR VI that can be calibrated against optical NDVI to create a daily time step of specific crop conditions.
- Demonstrate how to perform Sentinel-1 SAR preprocessing to derive quasi-polarimetric parameters.
- Perform a calibration of SAR VI to NDVI.

Climate Change and Agriculture

- Uncertainty remains regarding how climate change will impact agriculture.
- Understanding what has been "typical or normal" for a specific geography is important to develop adaptation strategies.

Opportunities

- Expansion of agriculture in certain regions
- Changes in temperature and precipitation can encourage planting of new crops in new regions

Challenges

- Increased intensity and frequency of droughts and violent storms, impacting yields and unseeded acres
- Greater prevalence of pests and pathogens; increased range, frequency and severity of insect and disease infestations




https://agriculture.canada.ca/en/environment/climate-scenarios-agriculture

Monitoring Crop Condition from Space

- The Normalized Difference Vegetation Index (NDVI) is used extensively by the agriculture sector as a proxy of crop condition and productivity.
- NDVI is the normalized ratio of red and infrared optical reflectance and is correlated with productivity indicators (e.g., Leaf Area Index, chlorophyll, and biomass).
- Globally, **operational monitoring systems** have been built based on time series NDVI (examples include U.S. Department of Agriculture VegScape (https://nassgeo.csiss.gmu.edu/VegScape/), the Group on Earth Observations (GEO) Global Agricultural Monitoring System (GLAM; https://cropmonitor.org/), and the Global Information and Early Warning System (GIEWS; https://www.fao.org/giews) of the United Nations.
- Typically, these operations provide a metric of current crop condition **relative to "normal"** conditions for a specific geographical location and time in the growing season.

The Canadian Crop Condition Assessment Program (CCAP)

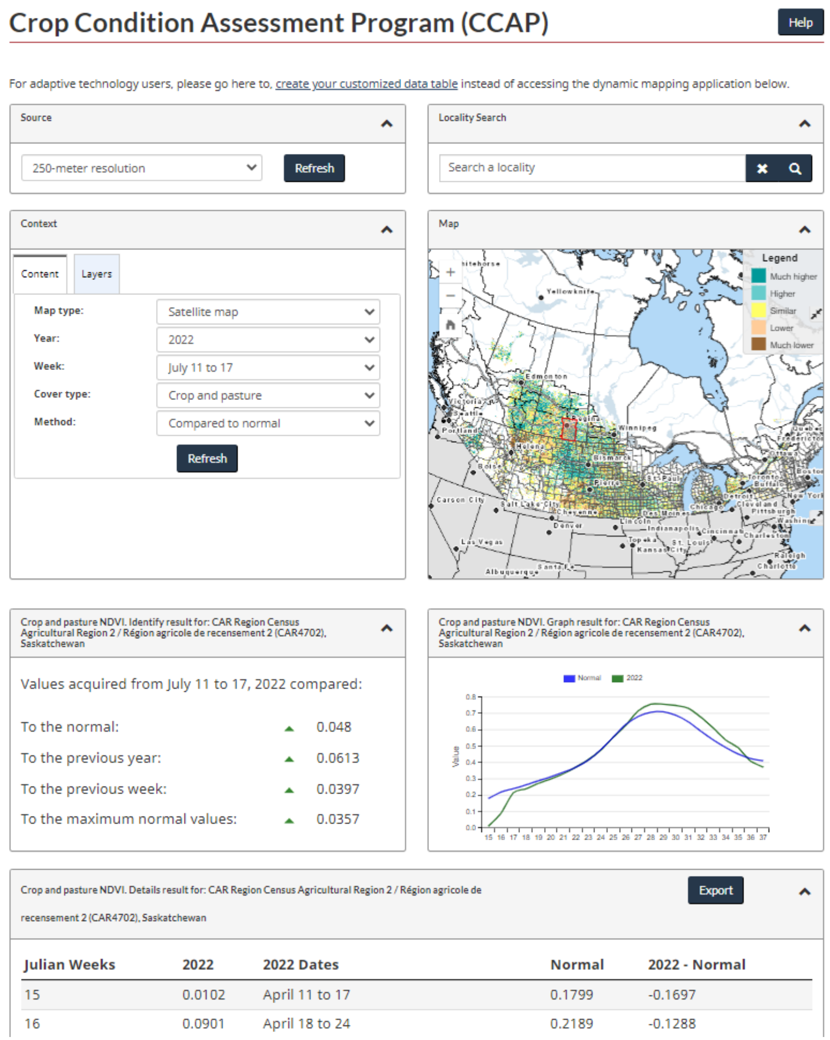
- As an example, Statistics Canada delivers a national operational crop condition monitoring system with the assistance of Agriculture and Agri-Food Canada.
- The Crop Condition Assessment Program (CCAP) is a very important service accessed by federal and provincial government agencies, grain marketing agencies, crop insurance companies, researchers, and producers.
- CCAP provides reliable, objective, and timely information on crop and pasture/rangeland conditions for Canadian agricultural lands and the northern portion of the United States.

https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=5177#a1

The Canadian Crop Condition Assessment Program (CCAP)

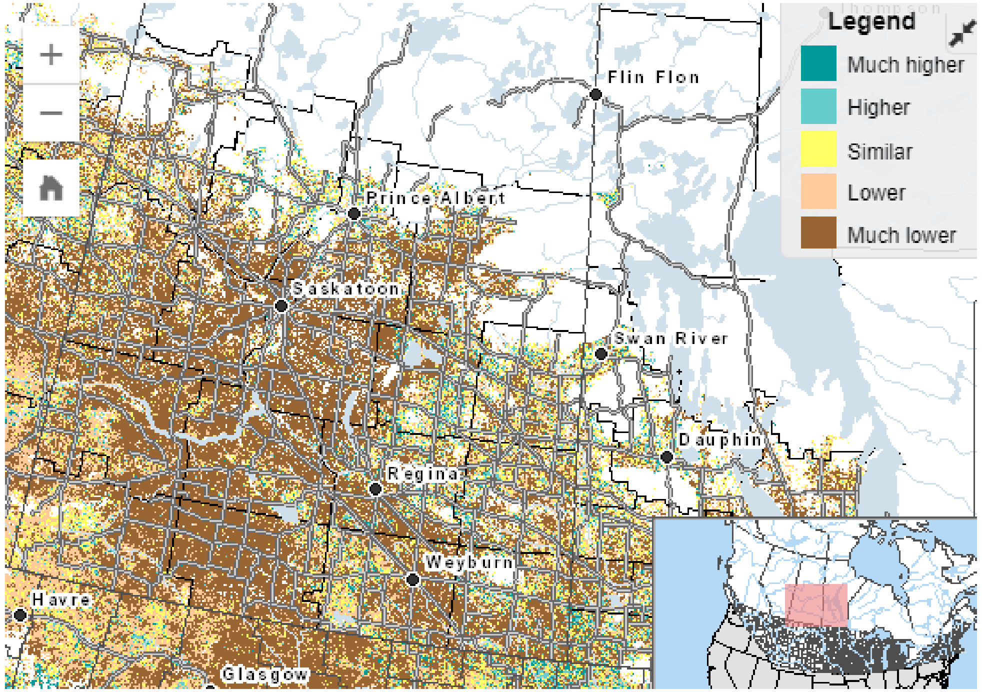
- CCAP estimates of NDVI are created using a 7-day composite of NOAA AVHRR images or MODIS.
- Image products are created **weekly** and delivered at a **250 m** spatial resolution; value-added products include charts, tabular data, and map products of average crop condition by administrative units.
- CCAP compares current conditions to the **historical normal** (back to 1987 for AVHRR and 2000 for MODIS).
- CCAP is run from Julian week 15 (which begins between April 6 and 12) to Julian week 41 (which begins between October 11 and 17).

https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=5177#a1



The Canadian Crop Condition Assessment Program (CCAP)

Optical NDVI (August 2–8, 2021) compared to normal

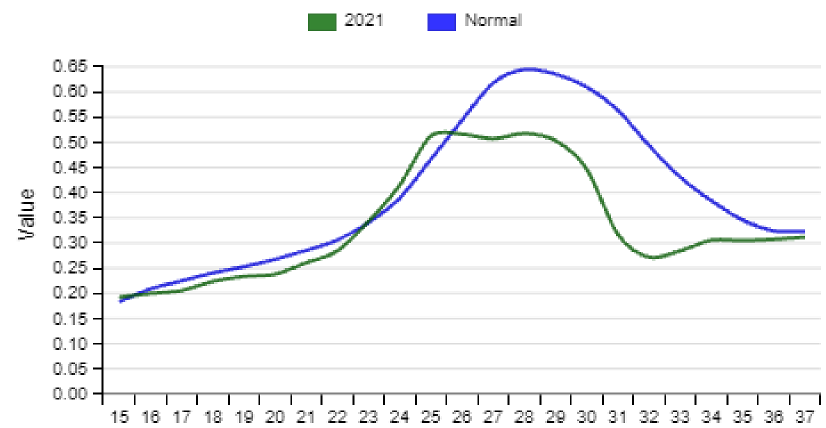


https://www35.statcan.gc.ca/CCAP/en/index#tbDetails

OTTAWA, Aug 30 (Reuters)
"Canola production in Canada plunged by 24.3% in 2021 compared to 2020 amid a bad drought while overall wheat production fell by 34.8%..."

"Farmers across Western Canada have had to contend with a lack of rain and higher-than-average temperatures throughout the growing season. This has exacerbated soil moisture conditions, which were already low at the start of the year," said Statscan. The survey was based in part on satellite and agroclimatic data.

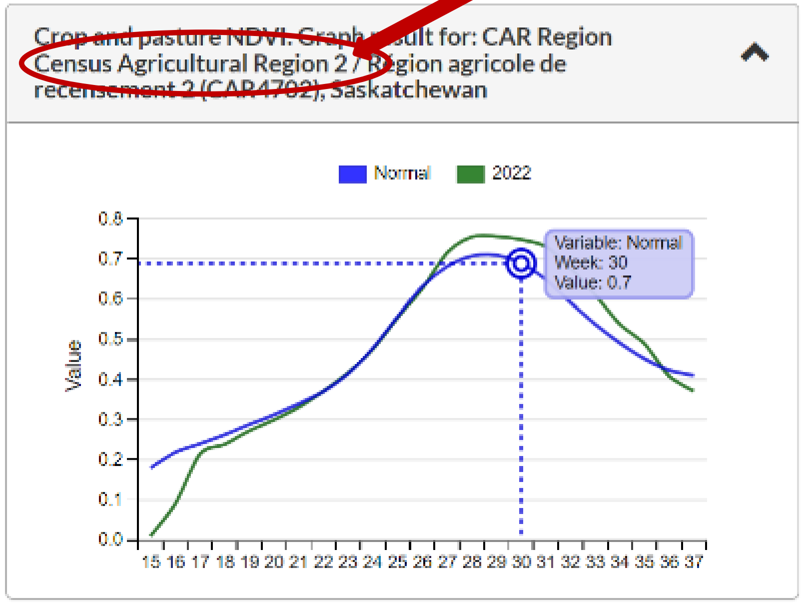
Crop NDVI. Graph result for: CCS Region Wood River No. 74 (CCS4703042), Saskatchewan



Limitations of Optical Based Crop Condition Monitoring

- One NDVI data point (per pixel/administrative unit) is provided each week.
- 7-day stacks are used to mitigate cloud cover (assume at least one AVHRR or MODIS pixel over 7 days will be cloud free).
- These stacks leverage optical satellites which provide a daily image, but at coarse spatial resolutions (250 m or larger).
- At this resolution it is difficult to assess field level crop condition and a single pixel may contain multiple fields and crop types.

https://geoprod.statcan.gc.ca/ccap/en/index



Crop and pasture NDVI. Identify result for: CAR Region Census Agricultural Region 2 / Région agricole de recensement 2 (CAR4702), Saskatchewan

Values acquired from July 11 to 17, 2022 compared:

To the normal:	▲	0.048
To the previous year:	▲	0.0613
To the previous week:	▲	0.0397
To the maximum normal	▲	0.0357

Monitoring Crop Condition Using Synthetic Aperture Radar (SAR)

- Research to develop a SAR-based Vegetation Index (SAR VI) is on-going. The Radar Vegetation Index (RVI) developed by Kim and van Zyl (2009) is an example.
- Agriculture and Agri-Food Canada has developed an alternate approach. It is **critical** that SAR estimates of crop condition can be integrated into NDVI-based operations that have run for decades.
    - Promotes uptake by community; it is not an option to replace current system.
    - Crop condition must be assessed against historical normal (optical NDVI based).
    - When MODIS replaced AVHRR, a calibration was done so that historical normal could continue to be leveraged. For CCAP, measure of normal (for specific week and geography) uses data from last 35 years
- Objective is to create a SAR VI that can be calibrated against optical NDVI and thus integrated into Canada's operational system.

SAR to Estimate Crop Condition

- Optical sensors
  - Visible-infrared reflectance responds to leaf pigmentation and the structure at both the leaf and canopy scales; **canopy structure** (leaf area and leaf orientation) also impacts reflectance measured at satellite scales.
- SAR sensors
  - Geometry of the target dictates not only the intensity of radar backscattering but also the angular scattering characteristics. The size, shape, and orientation of canopy components have a very significant impact on SAR responses.
  - SAR backscatter has been used to estimate crop biophysical parameters linked with **canopy structure** (leaf area and biomass).
- Polarimetry
  - Provides a more complete characterization of SAR response (not only backscatter intensity but also information about how canopy structure scatters waves).
  - Canopy structure is closely linked with crop development (phenology) and biomass accumulation.

Processing Flow for SAR

Fully polarimetric (Quad Pol)

- Transmit two orthogonally polarized waves (for example H and V); receive two orthogonally polarized waves (for example H and V); **measure and retain phase**
- Single Look Complex (SLC) data can be stored as a 3x3 covariance matrix with 9 elements to capture full scattering characteristics
- Examples: RADARSAT-2 or RADARSAT Constellation Mission (RCM) QP modes

“Quasi-” polarimetric (or “pseudo” pol)

- Transmit one polarization (for example V linear or circular) and receive two orthogonal polarized waves (for example V and H); **measure and retain phase**
- SLC data can be stored as a 2x2 covariance matrix with 4 elements to capture <u>some</u> scattering characteristics
- Examples: Sentinel-1 dual-pol SLC or RCM Compact Polarimetric mode

Pre-process SAR imagery and generate fully-polarimetric (i.e. RADARSAT) or quasi-polarimetric (i.e. Sentinel-1) parameters

↓

Feature Selection (Optional)

↓

Develop SAR Calibrated NDVI (SAR_{cal}-NDVI)

↓

Fit Crop Structure Dynamics Model (CSDM) to SAR_{cal}-NDVI

↓

Create temporal profile and map products of SAR_{cal}-NDVI

Sentinel-1 Single Look Complex (SLC) Data

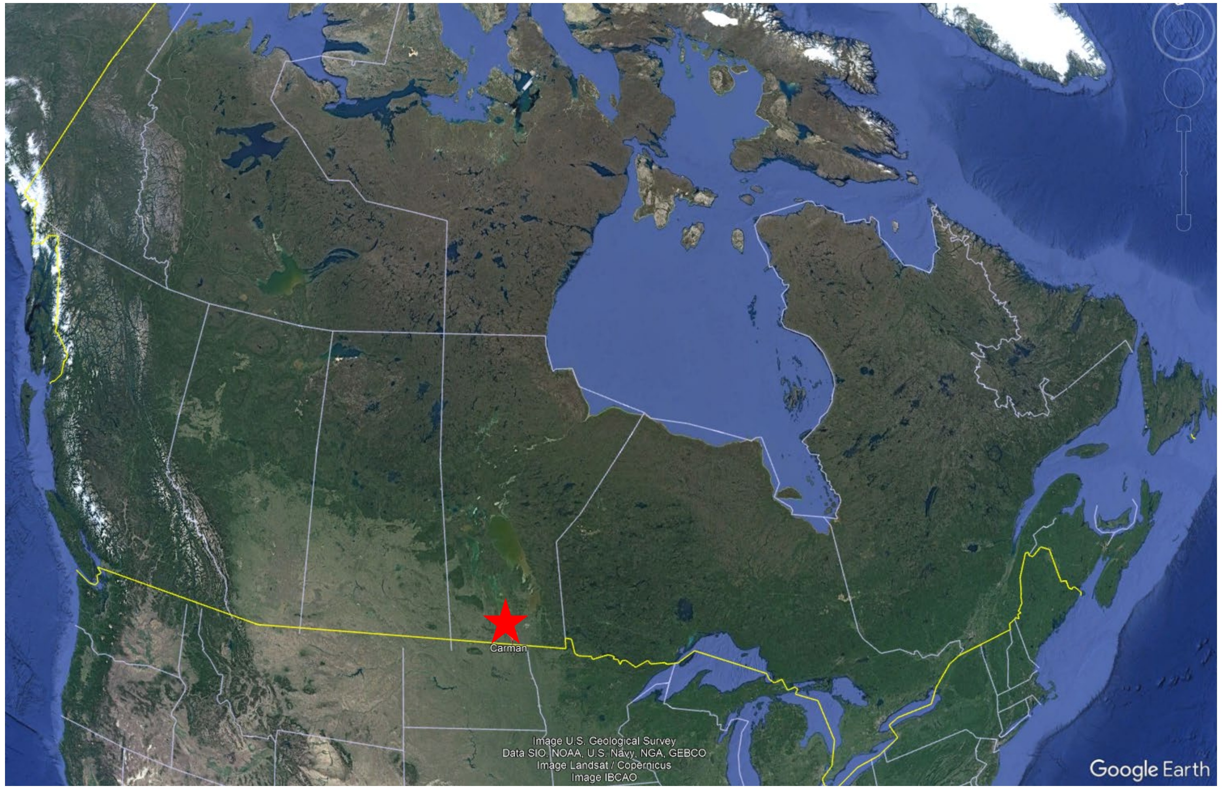
- AAFC has completed modeling for both RADARSAT-2 and Sentinel-1. The focus for this training will be Sentinel-1 given consistent coverage with this constellation.
- Sentinel-1 dual-pol (VV, VH) SLC data can be stored in a 2x2 covariance matrix [C2].
  - uses the full available signal bandwidth, and
  - phase is preserved and each pixel consists of both a real and imaginary component
- Using the 2x2 covariance matrix [C2] we are able to derive scattering parameters that are **similar** to fully polarimetric parameters.

$$C_2 = \begin{bmatrix} C_{11} C_{12} \\ C_{21} C_{22} \end{bmatrix} = \begin{bmatrix} |S_{vv}|^2 S_{vv} S_{vh}^* \\ S_{vh} S_{vv}^* |S_{vh}|^2 \end{bmatrix}$$

Selected Polarimetric Parameters

Linear polarization ratio (LPR)	The ratio of VV and VH intensities	
Span (I)	Total intensity (VV+VH), expressed in power	
Stokes parameters (S_0, S_1, S_2, S_3)	A set of values that describe the partial polarization state of an electromagnetic wave	$S_0 = \|E_H\|^2 + \|E_V\|^2 = C_{11} + C_{22}$ $S_1 = \|E_H\|^2 - \|E_V\|^2 = C_{11} - C_{22}$ $S_2 = 2\|E_H\|\|E_V\| \cos\emptyset_{HV} = 2Re(C_{12})$ $S_3 = 2\|E_H\|\|E_V\| \sin\emptyset_{HV} = 2Im(C_{12})$
Orientation angle (ψ)	The orientation of the linear polarization with the strongest backscatter	$\psi = \frac{1}{2}\tan^{-1}\frac{S_2}{S_1}$
Ellipticity angle (χ)	The ellipticity of the scattered wave	$\chi = \frac{1}{2}\tan^{-1}\frac{S_3}{\sqrt{S_1^2 + S_2^2}}$
Degree of polarization (DoP)	The ratio of polarized scattering to total scattering	$DoP = \frac{\sqrt{S_1^2 + S_2^2 + S_3^2}}{S_0}$
Degree of linear polarization (DoLP)	The degree of linear polarization components in the polarized scattering	$DoLP = \frac{\sqrt{S_1^2 + S_2^2}}{\sqrt{S_1^2 + S_2^2 + S_3^2}}$
Eigenvalues (l_1)	Eigenvalues of the coherency matrix	$l_1 = \frac{1}{2}(S_0 + mS_0)$
Eigenvalues (l_2)	Eigenvalues of the coherency matrix	$l_2 = \frac{1}{2}(S_0 - mS_0)$
Entropy (H)	The degree of randomness of scattering	See Cloude, et al. 2012 https://www.researchgate.net/publication/260622729_Compact_Decomposition_Theory
Alpha ($\bar{\alpha}$)	The dominant scattering mechanism (in degrees)	See Cloude, et al. 2012 https://www.researchgate.net/publication/260622729_Compact_Decomposition_Theory
Normalized Shannon Entropy (SE)	The sum of total backscatter power and the Barakat degree of polarization, normalized to between 0 and 1	See Réfrégier and Morio 2006 https://www.researchgate.net/publication/6692148_Shannon_entropy_of_partially_polarized_and_partially_coherent_light_with_Gaussian_fluctuations

Study Site – Carman/Elm Creek Manitoba (Canada)



Carman, Manitoba (Canada)

soybeans

wheat

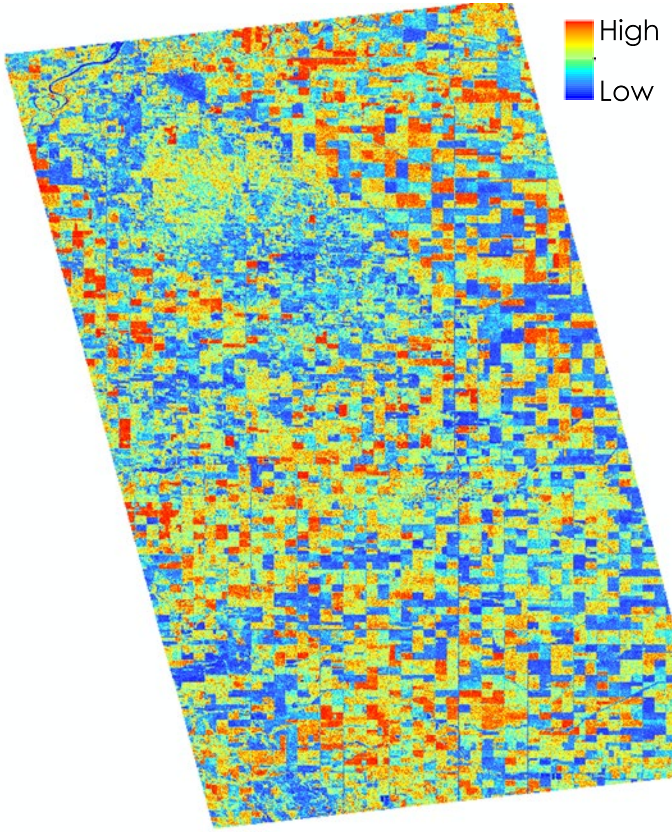
canola

corn

Vastly differing canopy structures

Intensity Parameters

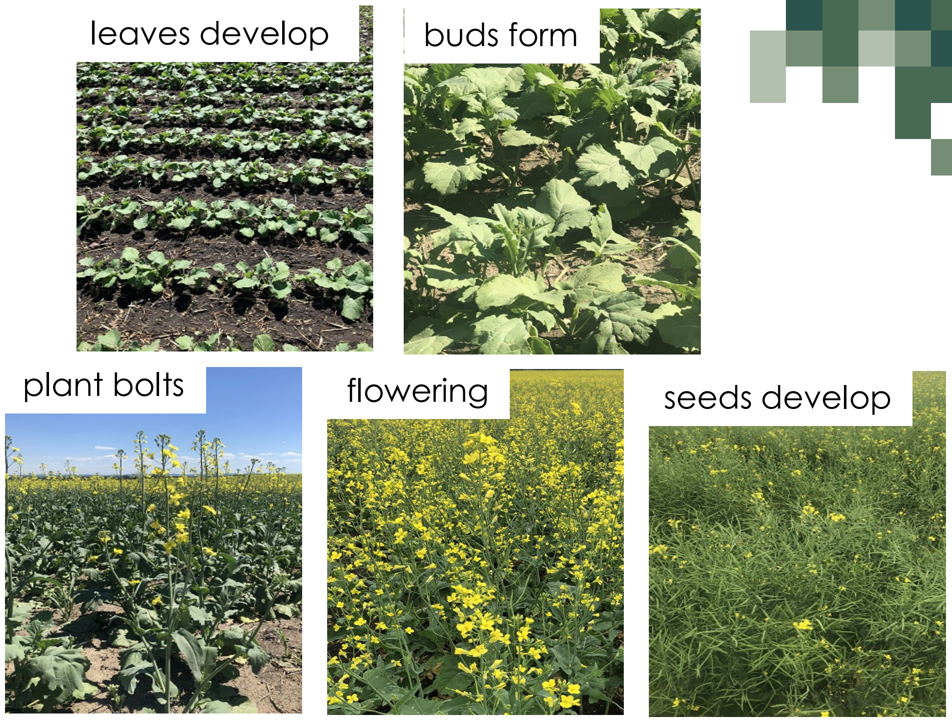
- Backscatter intensity (VV and VH) and polarization ratio (VV/VH)
- Total power (Span)
  - The total power (intensity) received by the four channels of a fully polarimetric radar system or two channels for quasi-polarimetric.
  - Fully polarimetric: HH + HV + VH + VV
  - Quasi polarimetric (assuming V transmit and V+H on receive): VV+VH
- Low Span for bare soils due to the quasi-specular reflection of the SAR waves.
- High Span for land covers with more vegetation due to the high radar return linked to volume scattering.
- Sentinel-1: no HH intensity recorded but this is typically a less important intensity when considering agricultural land cover.

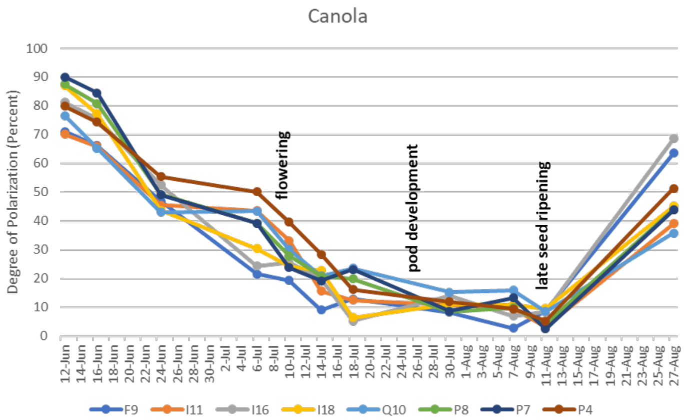


Carman, Manitoba, Canada
S_0 or Span (VV+VH)
Sentinel-1 (August 8, 2019)

Degree of Polarization (DoP)

- A propagated wave is completely polarized.
- If the target is composed of elements with varying orientations (leaves, stalks, flowers, etc.) waves scattered by these individual elements will vary in phase and polarization.
- These multiple scattering events result in a scattered wave that is partially polarized and partially unpolarized, measured as the **DoP.**
- The ratio varies among crop types and changes as crops grow (different phenology and canopy conditions).
- DoP is high early in season and after harvest when vegetation cover is low; DoP decreases as crops grow.



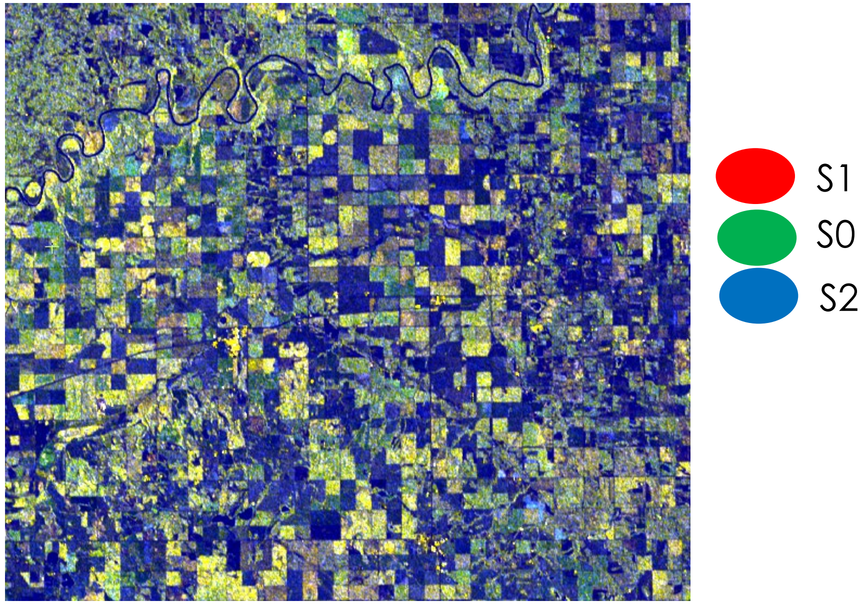


Changes in DoP as Crops Develop
RCM Compact Polarimetric Data
(Dingle Robertson et al., 2022)

Stokes Parameters

- First Stokes vector parameter (S_0) represents the total intensity of the radar backscatter (polarized and unpolarized), which is the sum of the powers of the two orthogonally-polarized received waves.

- Other three parameters (S_1, S_2, and S_3) describe the properties of the **polarized** portion of the EM field.



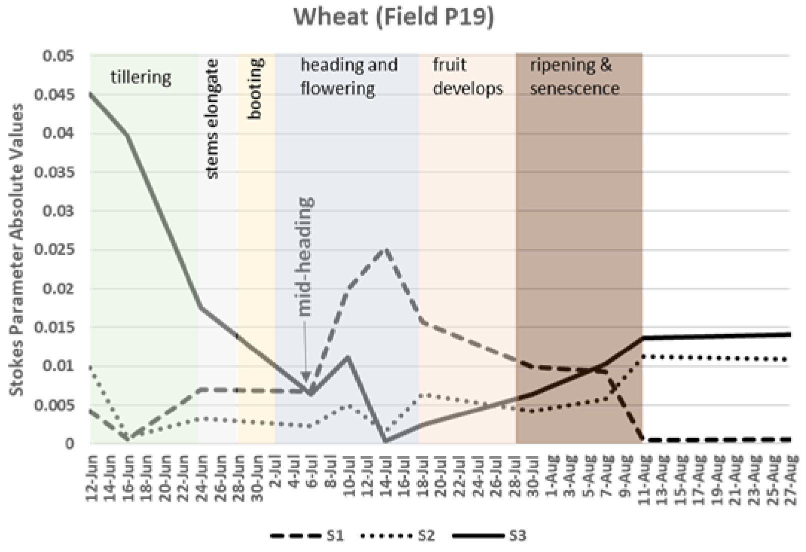
July 9th, 2020, Sentinel-1 Stokes
Carman Manitoba

Stokes Parameters

- S1, S2, and S3 need to be interpreted together.

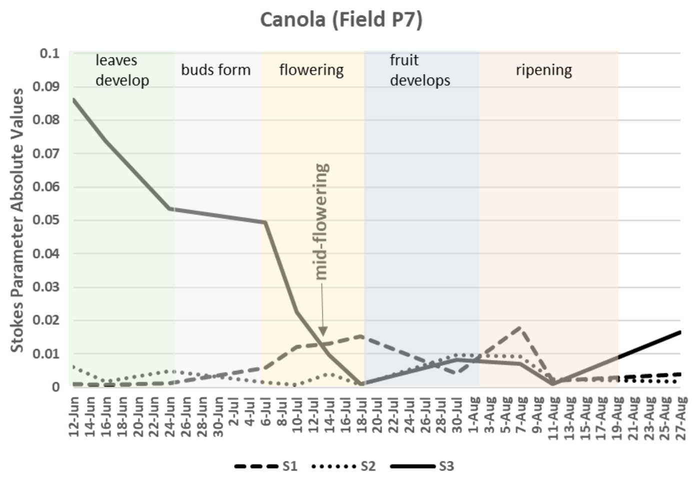
S1 – difference in powers of received channels (H and V)
S2 – dominance of linear +45° over linear -45°
S3 – dominance of right-handed circular over left-handed circular

- Behavior of Stokes parameters changes as crop structure changes (accumulation of leaves and stems, development of flowers, fruit and seeds).



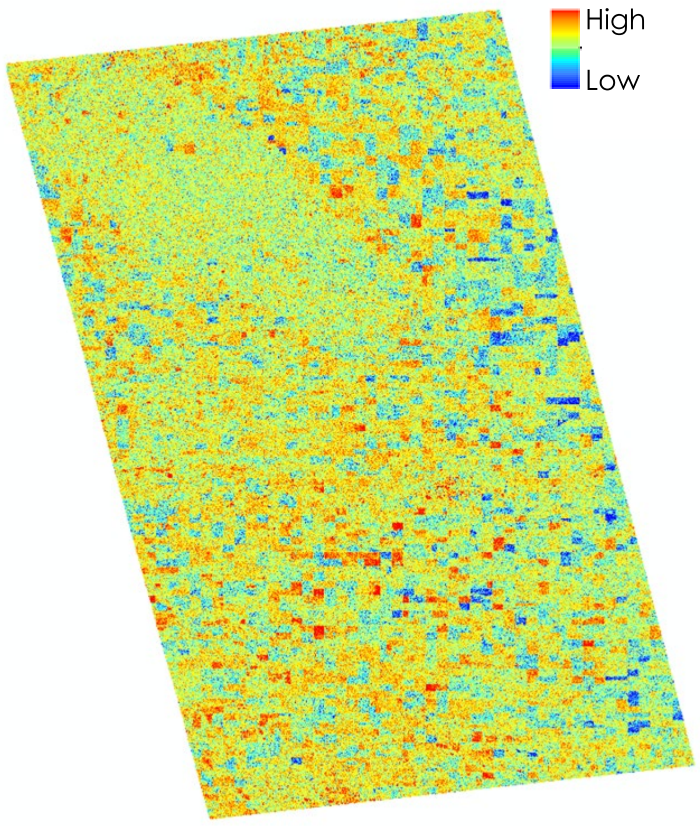
Changes in Stokes Parameters as Crops Develop

RCM Compact Polarimetric Data (Dingle Robertson et al., 2022)



Degree of Linear Polarization (DoLP)

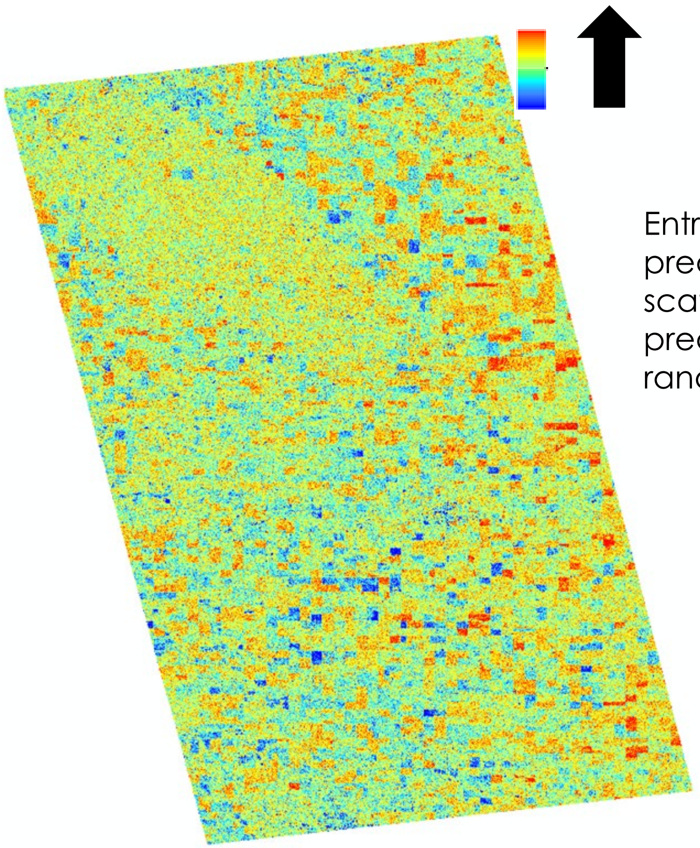
- In contrast to DoP, the degree of linear polarization (**DoLP**) references only the polarized scattering and measures the percentage of this polarized energy which is linearly polarized (regardless of the orientation angle of these linear waves).
- If there are linear features in the canopy, linear polarization may dominate scattering (high DoLP).
- Differences in structure (from crop to crop; as crops grow) will change DoLP.



Carman, Manitoba, Canada
Degree of Linear Polarization (DoLP)
Sentinel-1 (August 8, 2019)

Entropy

- Cloude et al. (2012), Cloude (2007) developed a dual-polarized version of the fully polarimetric H/α/A decomposition method, which only includes entropy (H) & alpha(α).
- Entropy is a measure of randomness of scatter from point to point within the target, with **the predictability in scattering characteristics declining as crop canopies develop.**
- Shannon entropy (SE) was introduced by (Réfrégier and Morio, 2006; Morio et al., 2007). SE is the sum of two contributions related to the intensity (SE_i) and the degree of polarization (SE_p).



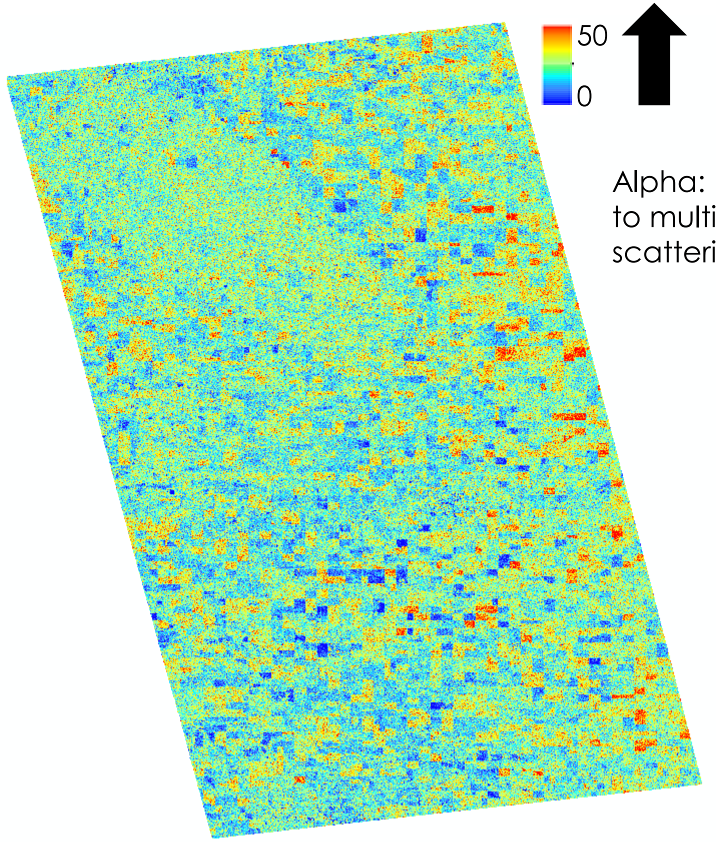
Entropy: From predictable scattering to less predictable (more random) scattering.

Carman, Manitoba, Canada
Sentinel-1 (August 8, 2019)

Alpha

- Crop canopies result in a mixture of scattering mechanisms (single, double, multiple), although one type of scattering typically dominates.

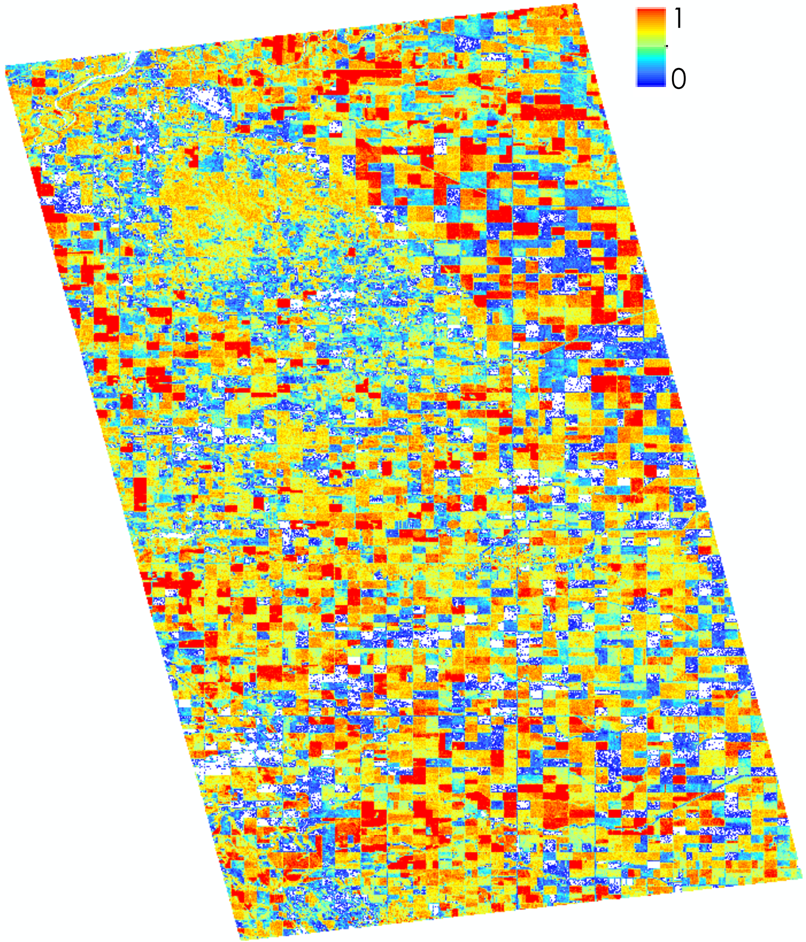
- Alpha angle indicates which of these scattering mechanisms dominate; as canopies develop the contributions from multiple and double bounce typically increase.



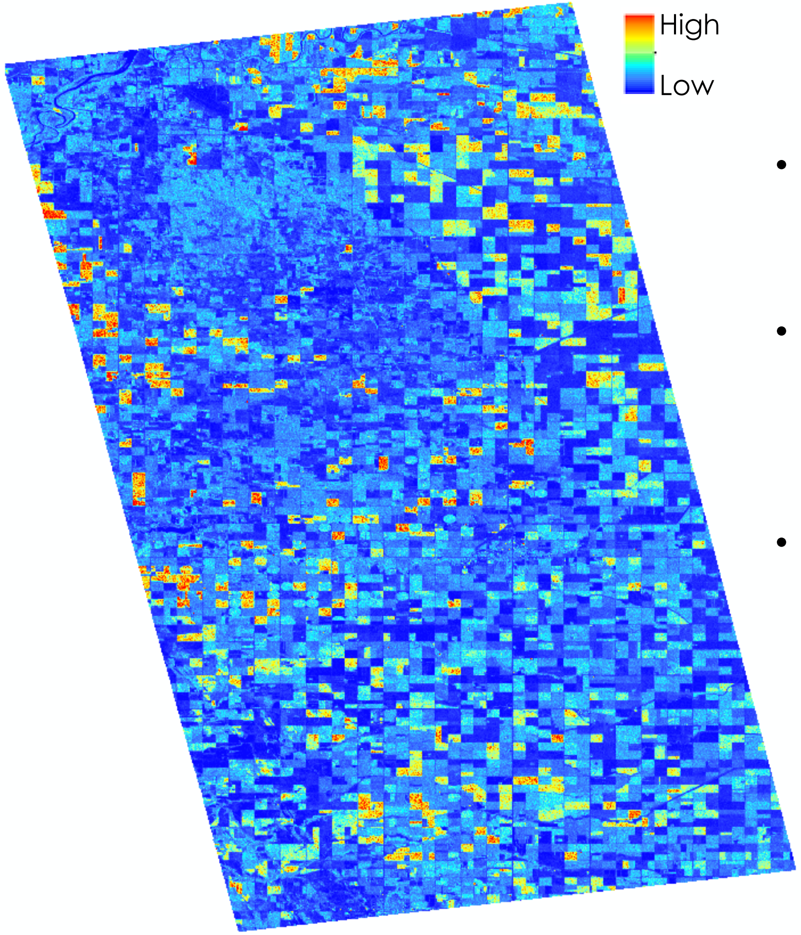
Alpha: From surface to multiple/volume scattering

Carman, Manitoba, Canada
Sentinel-1 (August 8, 2019)

Selected as High Importance for Modeling Crop Condition



Carman, Manitoba, Canada
Normalized Shannon Entropy
Sentinel-1 (August 8, 2019)



Carman, Manitoba, Canada
Second Eigenvalue (I2)
Sentinel-1 (August 8, 2019)

- Sum of the first and second eigenvalues (I1 and I2) equals the total backscatter intensity.
- Second eigenvalue expresses half of the intensity of the unpolarized component of the scattered wave.
- While DoLP describes the linearity of the polarized scattering, I2 captures the amount of unpolarized scattering.

Parameter Feature Selection

- All Sentinel-1 SAR parameters are derived from 2x2 covariance matrix.
- Parameters can be cross-correlated and offer redundant information.
- Using a “large” number of variables can result in model overfitting.

- SAR parameter feature selection is optional (pre-select features or allow machine learning models to select best features).
- Many options for feature selection (Least Absolute Shrinkage and Selection Operator [LASSO] is one example).

Develop SAR Calibrated NDVI (SAR_{cal}-NDVI)

Data sources: Sentinel-1 SLC and Sentinel-2 (AAFC has also tested RADARSAT-2 QP)

Crop types: corn, canola, wheat, soybeans, barley and oats

Pre-Processing

- Derive SAR polarimetric parameters (Sentinel-1) and NDVI (Sentinel-2).
- Feature selection is optional.
- Create image segments (from Sentinel-2 NDVI product).
- Calculate mean SAR response and mean NDVI per image segment (on crop-by-crop basis; also, all crops).
- Using segments (not pixels) to reduce residual SAR noise.

Create calibration function (multiple SAR parameters to NDVI) using machine learning algorithms.

- Machine learning models:
  - Feed Forward Artificial Neural Network (ANN)
  - Least Square Boost Regression (LSBoost)
  - Random Forest Regression (RFR)

- Given its easy and successful implementation, **RFR will be demonstrated in this training.**

Coefficients of Determination (R^2)
Sentinel-1 Parameters and
Sentinel-2 NDVI
Validation Results

Canola	0.782
Corn	0.808
Soybeans	0.883
Wheat	0.859
All Crops	0.663

Fit SAR_{cal}-NDVI to Crop Structure Dynamics Model

- A Crop Structure Dynamics Model (CSDM) is used to fit SAR VI estimates to create a daily time step of crop condition.
- This approach improves temporal (daily) and spatial (sub-field) estimates of crop condition .

$$D = D_{max}\left[\frac{1}{1+e^{-b(T-T_i)}} - e^{-a(T-T_s)}\right]$$

D: canopy structural descriptor with a maximum achievable value D_{max} . D is set as SAR_{cal}-NDVI

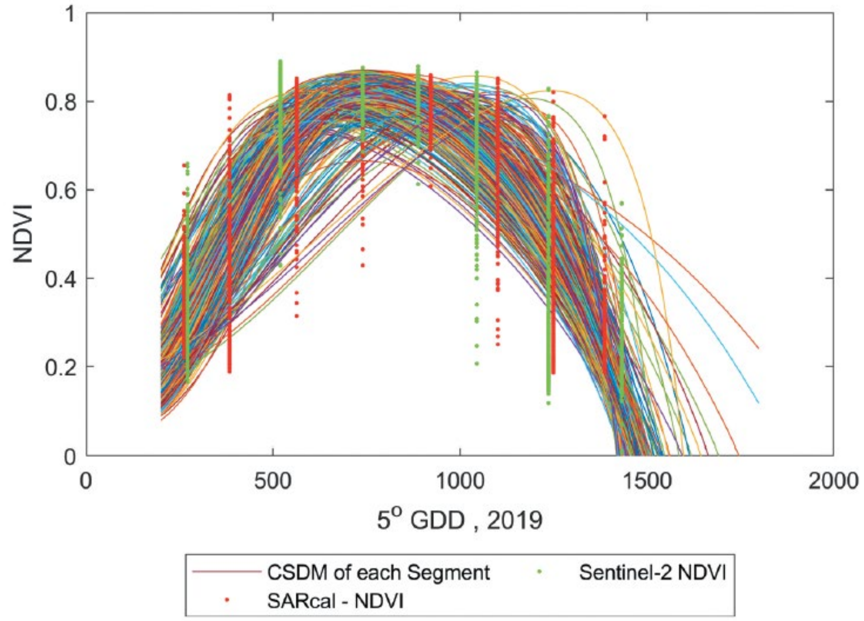
T: the accumulative Growing Degree Days (GDD; for Canada, set to May 1)

The model describes the canopy structure in two parts: growth and senescence.

The growth period is defined by a logistic equation with parameters b and T_i. The coefficient b is the relative growth rate at the inflection point T_i.

The senescence is defined by an exponential equation with parameter a and T_s. a is the senescence rate. T_s represents the accumulative GDD at which D decreases to 0 due to senescence.

- Programmed in MATLAB
- Five coefficients (D_{max}, a, b, T_i and T_s) optimized using the Levenberg-Marquardt least squares method.



Green dots: NDVI from Sentinel-2
Red dots: SAR_{cal}-NDVI from Sentinel-1

Lines: CSDM fit for each sub-field object (Jiao et al., 2022)

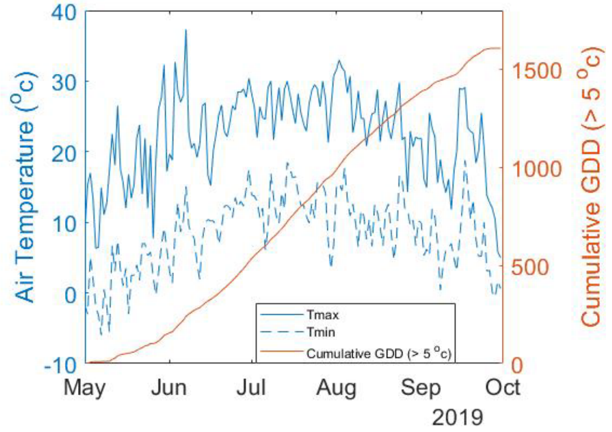
Growing Degree Days (GDD)

- GDDs are the average daily maximum (T_{max}) and minimum (T_{min}) temperatures minus the base temperature (T_{base}).
- Base temperature is a threshold below which little growth occurs and varies by crop type.
- We set the base temperature for this region of Canada to 5°C.
- Daily maximum and minimum temperatures downloaded from nearby meteorological station.

$$GDD = (T_{max} + T_{min})/2 - T_{base}$$

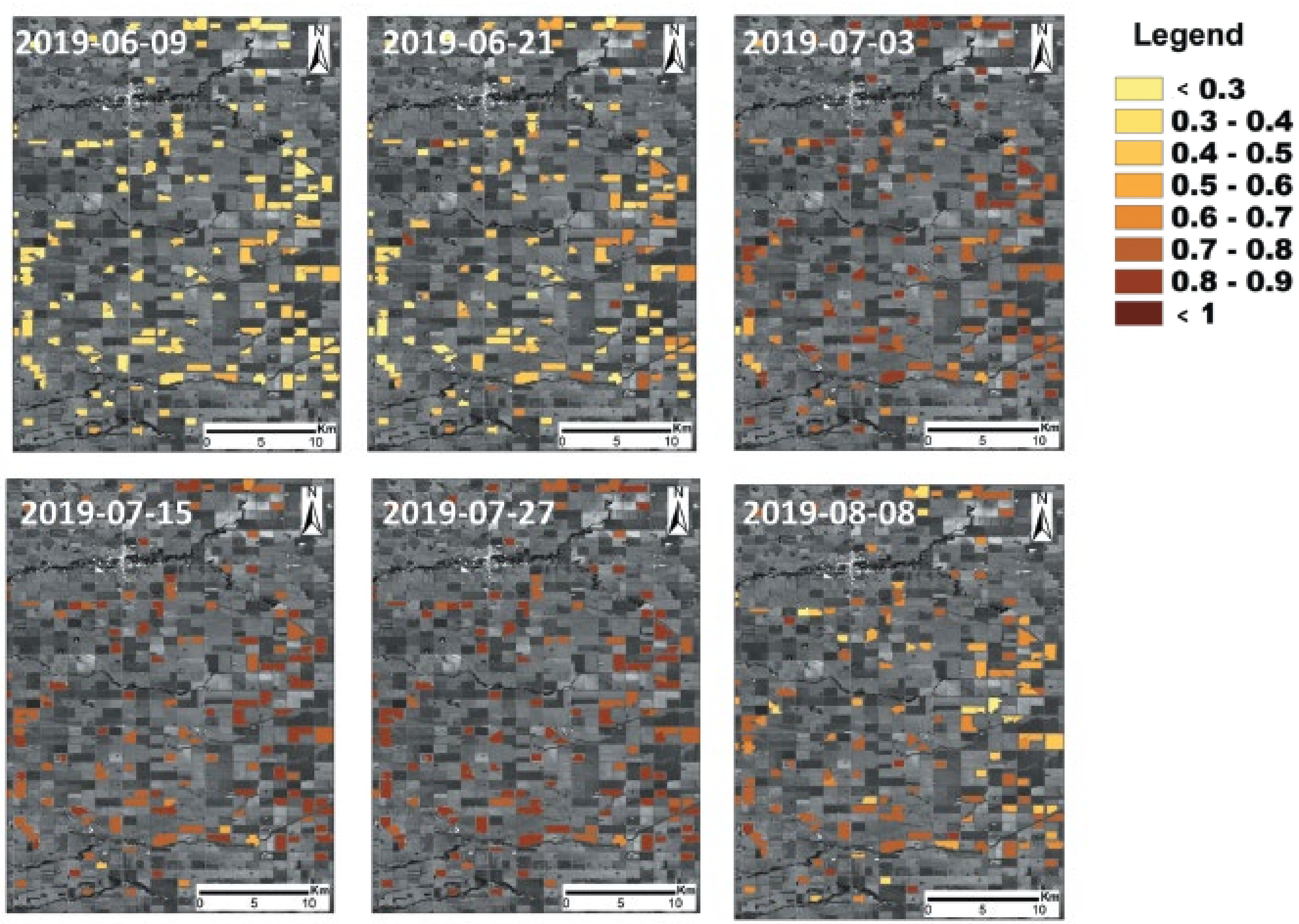
Where if $[(T_{max} + T_{min})/2 < T_{base}]$, then GDD = 0

- Accumulated GDD is calculated by summing GDDs for each day during growing season.



Example of GDD accumulation over Canadian growing season (Jiao et al., 2021)

Creation of SAR_{cal}-NDVI Time Series



Tracking of canola crop development throughout 2019 growing season using Sentinel-1
(Jiao et al., 2022)

- It is important to validate SAR based estimates of crop condition to biophysical measures.
- This is ongoing but for canola, correlation (R^2) between Sentinel-1 based SAR_{cal}-NDVI and field measured biomass has been completed.
- From early to mid season (period of rapid biomass accumulation) R^2 is 0.88.
- From mid to late season (period of senescence) R^2 is 0.42. Lower correlation is related to the fact that biomass remains stable, but crop water content is declining.

References

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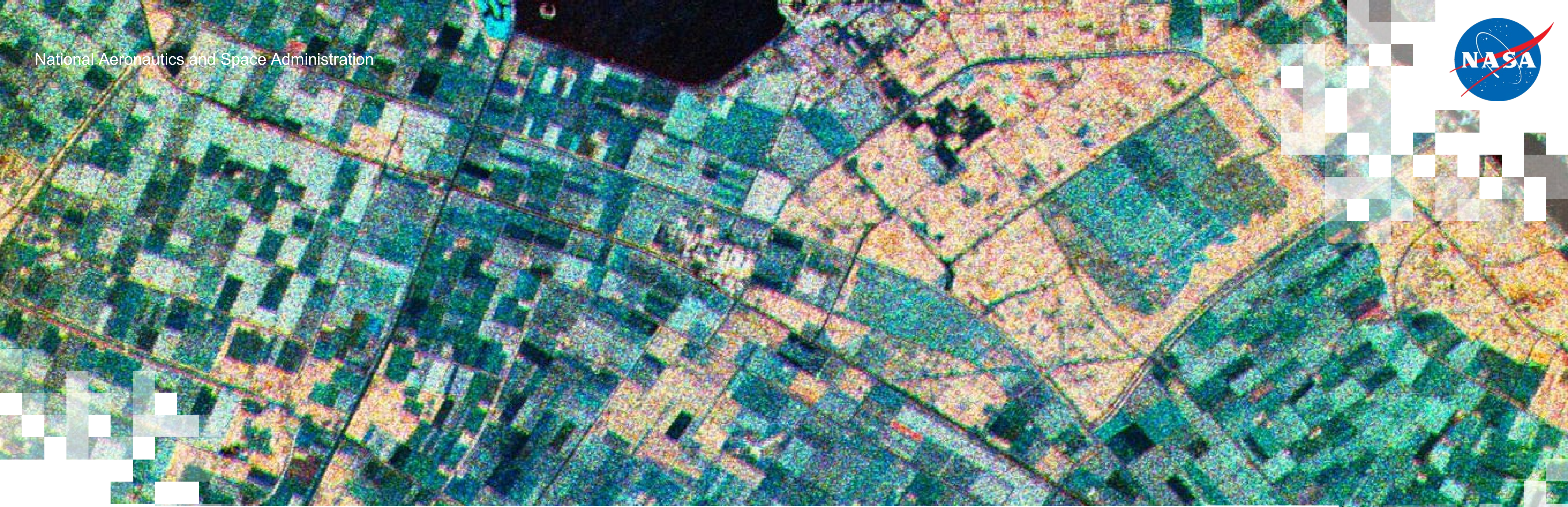
Réfrégier, P., and Morio, J. (2006). "Shannon Entropy of Partially Polarized and Partially Coherent Light with Gaussian Fluctuations." Journal of the Optical Society of America 23 (12): 8. doi:10.1364/ JOSAA.23.003036.



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Monitoring Crop Growth Through SAR-Derived Structural Parameters

APPLIED REMOTE SENSING TRAINING PROGRAM
TRAIN - EMPOWER - ADVANCE

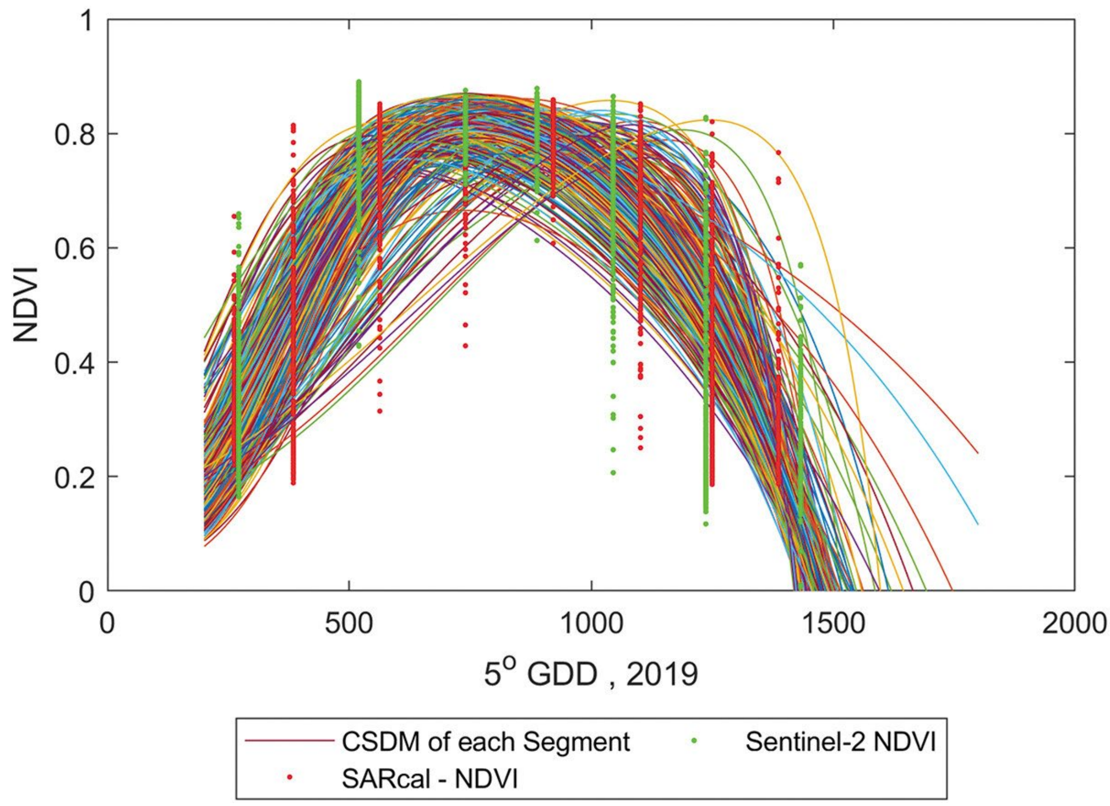
Emily Lindsay, Heather McNairn, and Xianfeng Jiao – Agriculture and Agri-Food Canada

April 11, 2023

Outline

Hands-on Exercise (Emily Lindsay)

- Sentinel-1 SAR preprocessing
  - SNAP
- Deriving quasi-polarimetric parameters from Sentinel-1 Single Look Complex (SLC) data
  - PolSARpro
- Random Forest Regression for SAR_{cal}-NDVI
  - Python
- SARcal-NDVI to CSDM
  - MATLAB



Green dots: NDVI from Sentinel-2
Red dots: SAR_{cal}-NDVI from Sentinel-1

Lines: CSDM fit for each sub-field object
(Jiao et al., 2022)

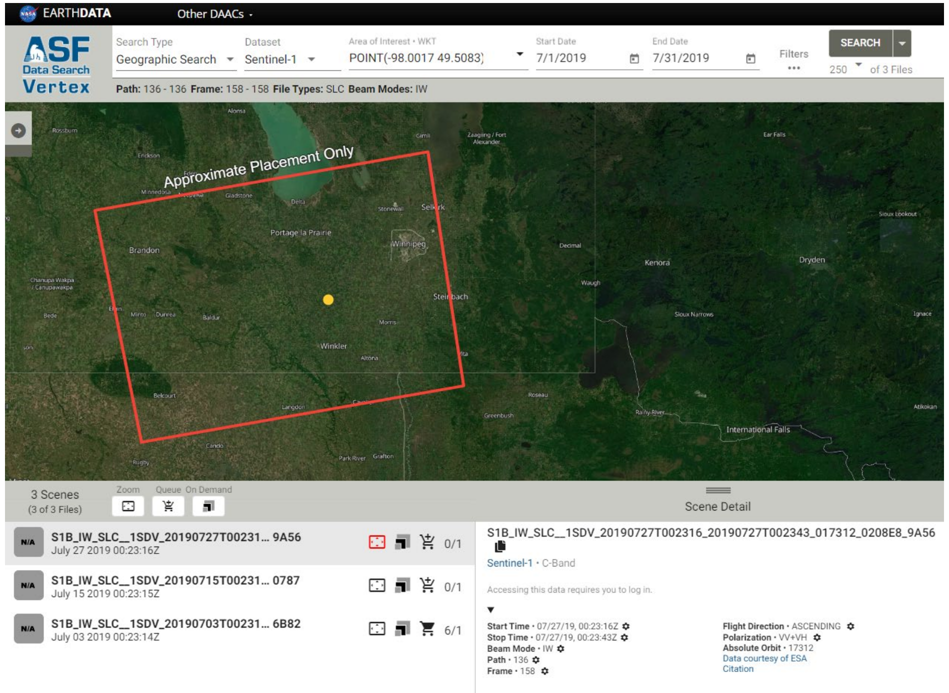
Sentinel 1 SLC Imagery

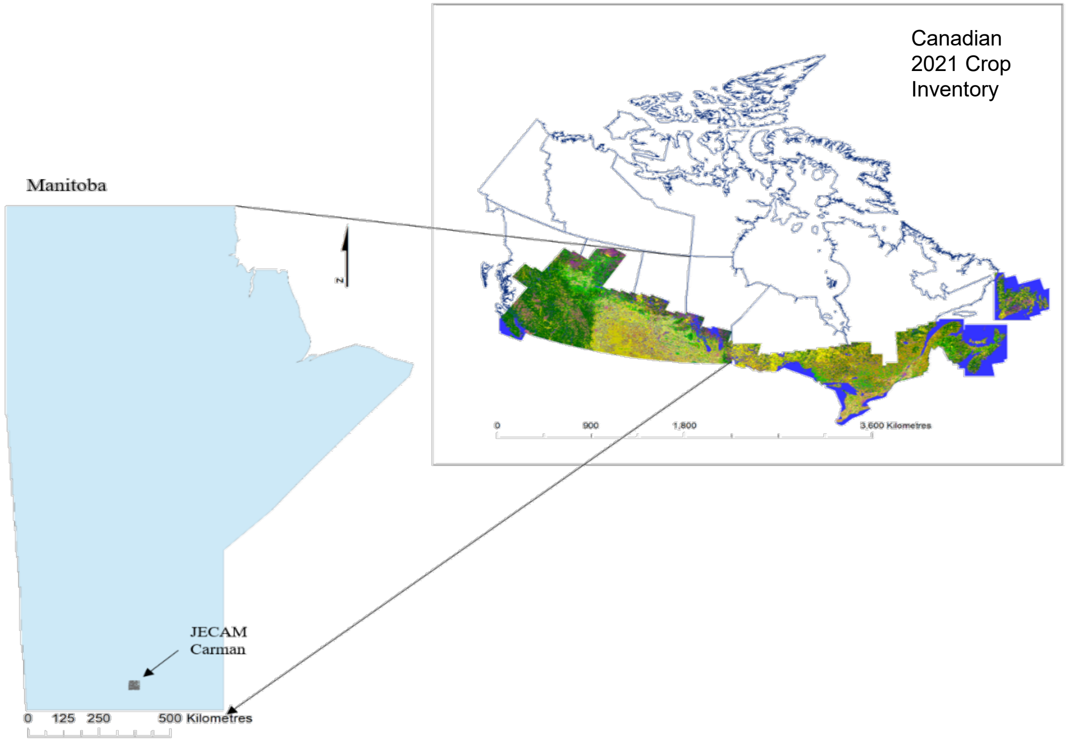
S1B_IW_SLC__1SDV_20190727T002316_20190727T002343_017312_0208E8_9A56

- Carman, MB JECAM site
- July 27, 2019, S1 **SLC** Image
- ASF Vertex: https://search.asf.alaska.edu/#/
- Corresponding S2 Image (~2-3 day of S1, cloud-free) to calculate NDVI

$$\mathbf{C}_2 = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \begin{bmatrix} \langle |S_{VV}|^2 \rangle & \langle S_{VV} S_{VH}^* \rangle \\ \langle S_{VH} S_{VV}^* \rangle & \langle |S_{VH}|^2 \rangle \end{bmatrix}$$

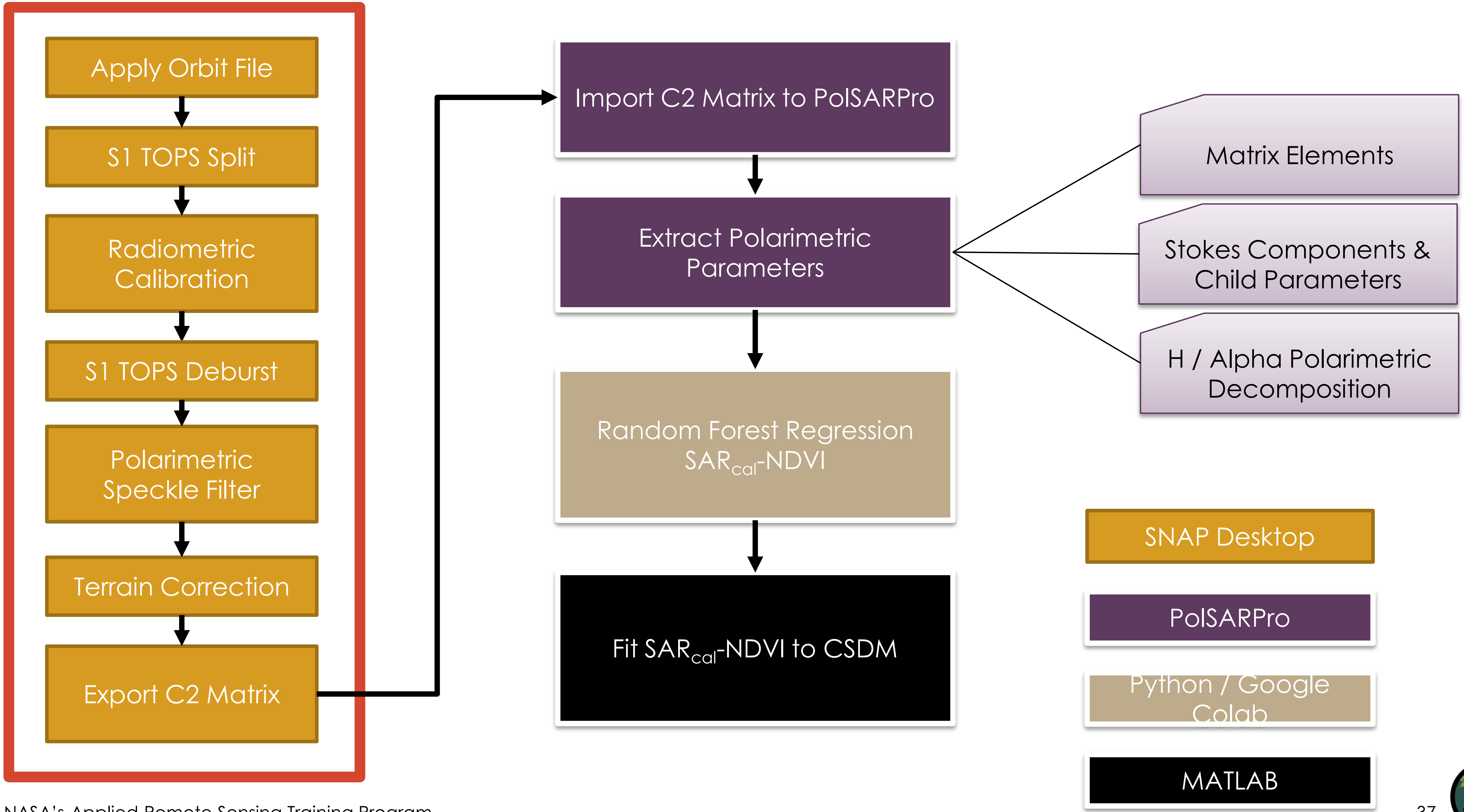
ASF Data Search Vertex





https://scihub.copernicus.eu/dhus/#/home

Processing Methodology



1. Generate C2 Matrix in SNAP

Apply Orbit File

Orbit information of Sentinel-1 can be downloaded from ESA: https://scihub.copernicus.eu/gnss/#/home.

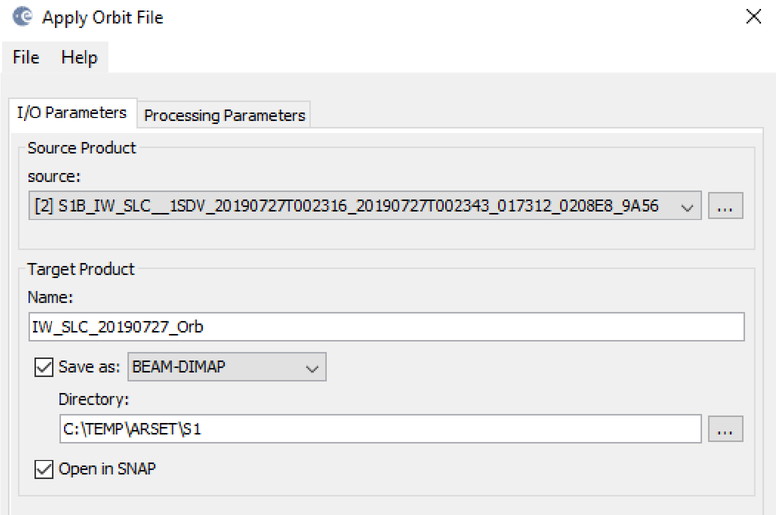
Radar → Apply Orbit File

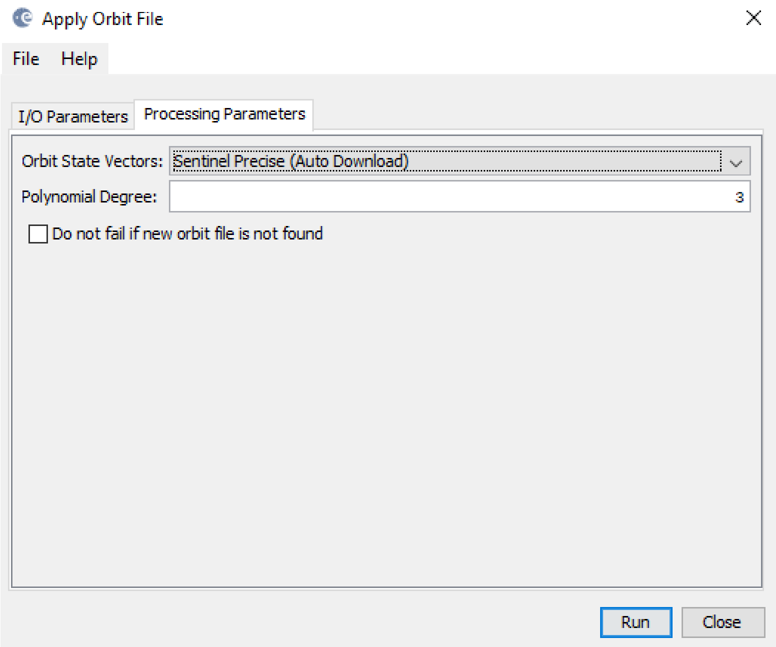
I/O Parameters:

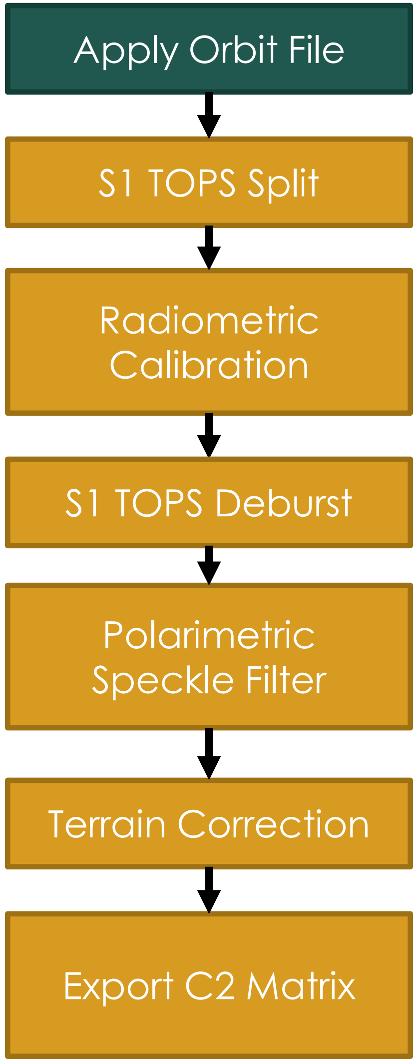
- Input: S1 .Zip file

Processing Parameters:

- Orbit State vectors: Sentinel Precise (Auto Download)







1. Generate C2 Matrix in SNAP

S1 TOPS Split

TOPSAR Split to reduce processing time and memory requirements

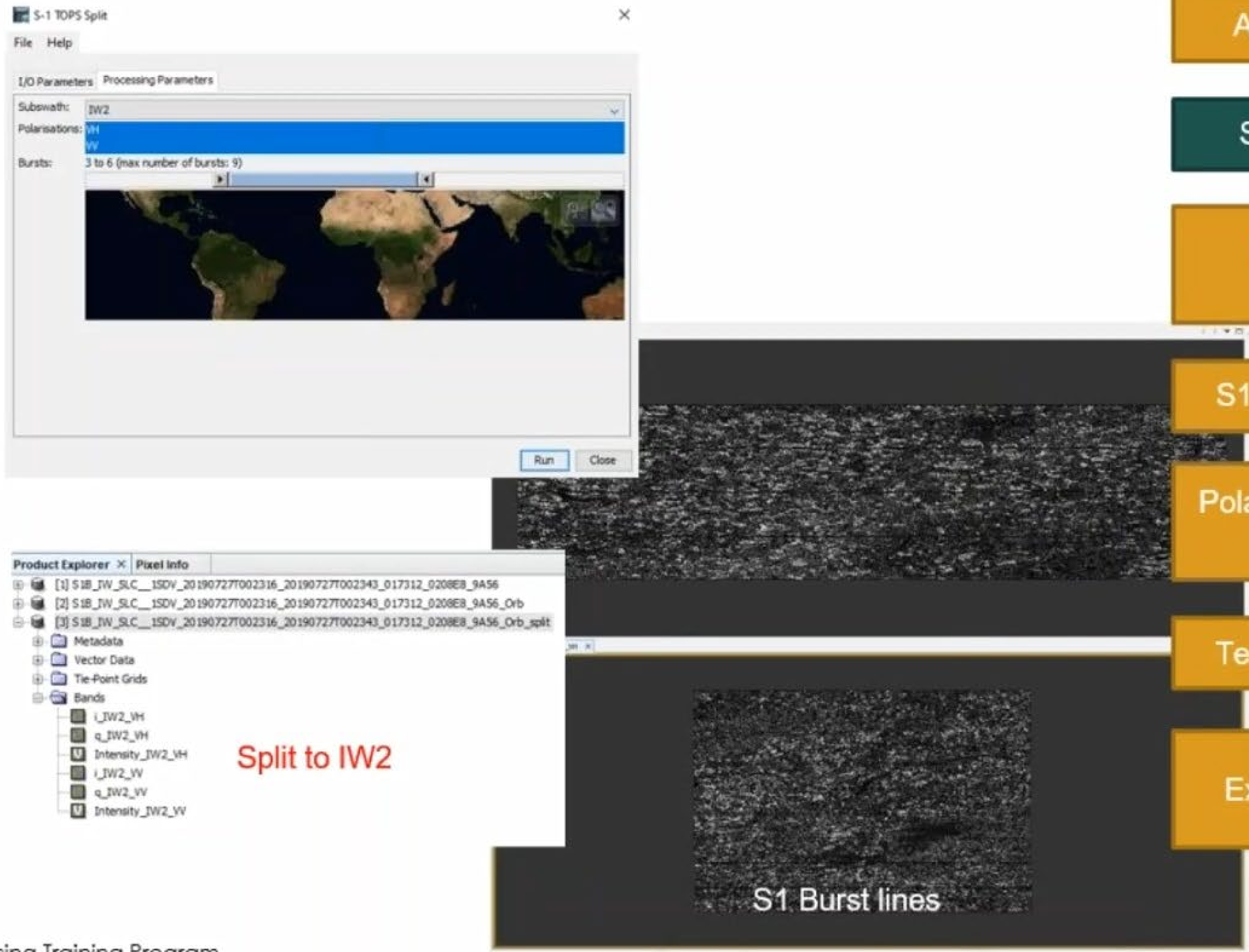
Radar → Sentinel-1 TOPS → S-1 TOPS Split

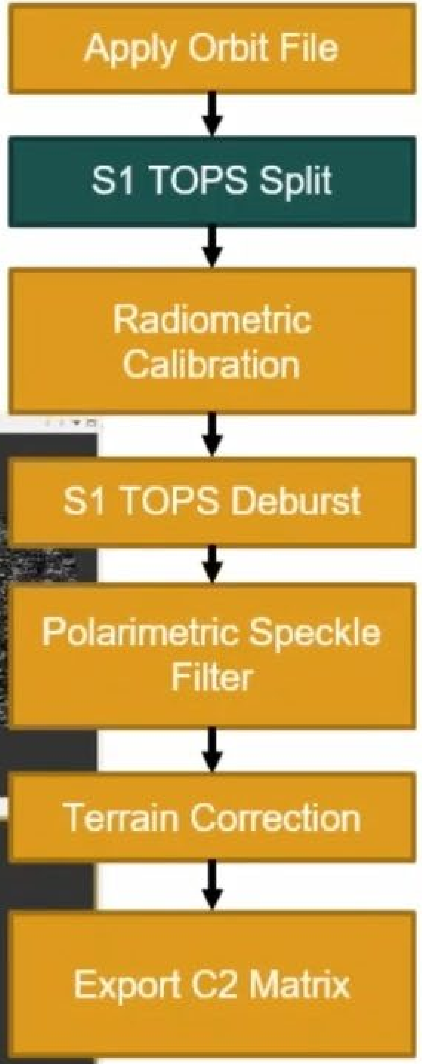
I/O Parameters:

- Orbit corrected image (Input)

Processing Parameters:

- Choose Subswath (IW1, IW2 or IW3)
- Select both polarizations
- Reduce Bursts using arrow sliders





1. Generate C2 Matrix in SNAP

Radiometric Calibration

Convert SAR SLC complex data to radar backscatter (σ°) real (intensity) and imaginary (phase) channels.

SNAP will automatically determine the conversion based on S1 SLC product metadata.

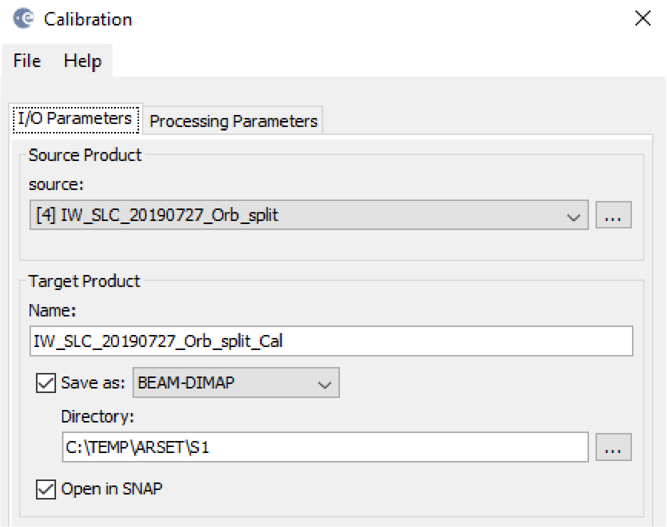
Radar → Radiometric → Calibrate

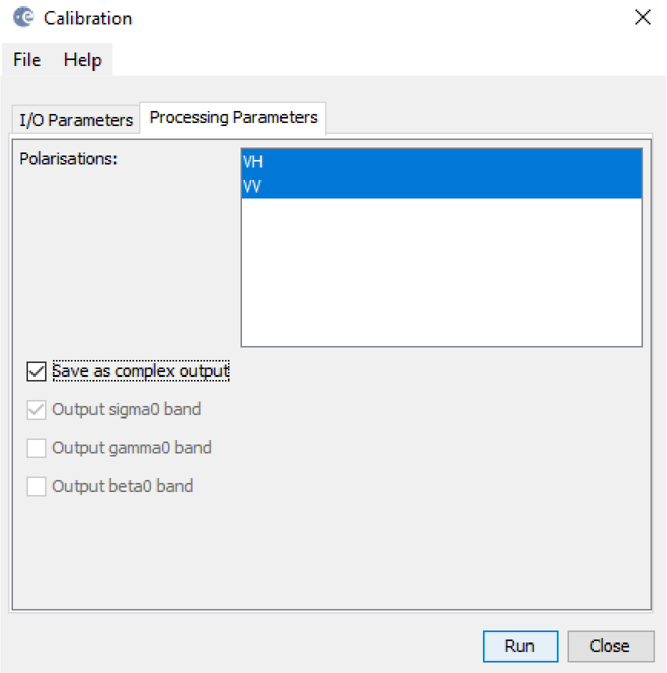
I/O Parameters:

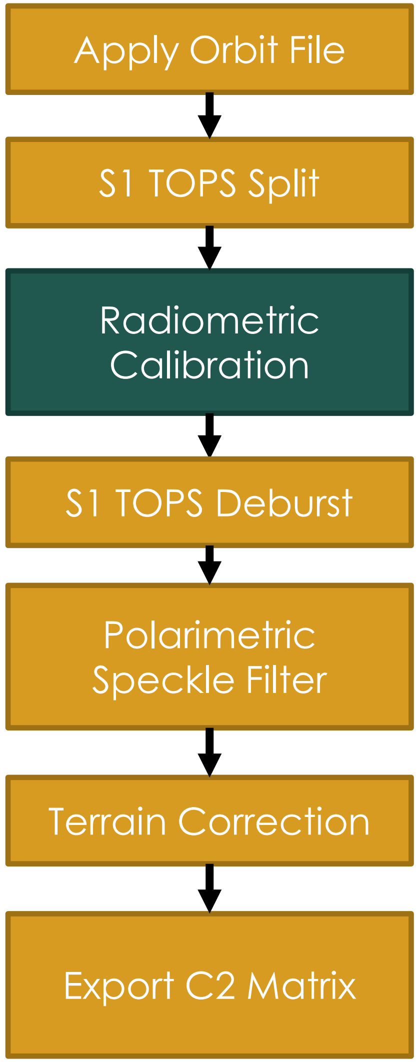
- Input: Split file

Processing Parameters:

- Select both polarizations and select save as complex output







1. Generate C2 Matrix in SNAP

S1 TOPS Deburst

Resampling and merging of the selected subswath(s) and bursts. Resamples to a common pixel spacing grid and removes burst lines.

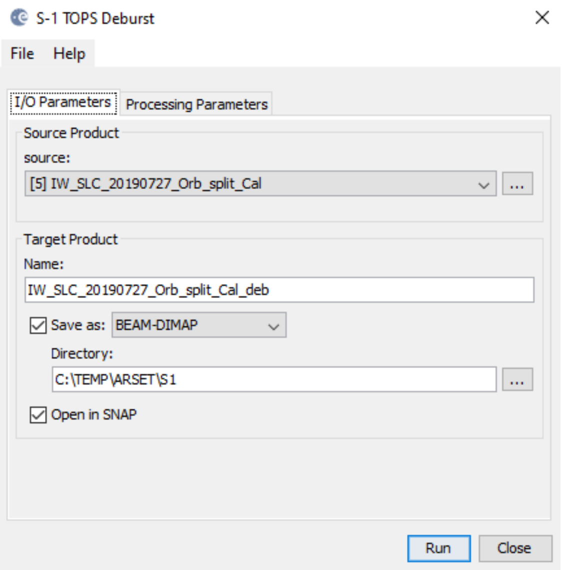
Radar → Sentinel-1 TOPS → S-1 TOPS Deburst

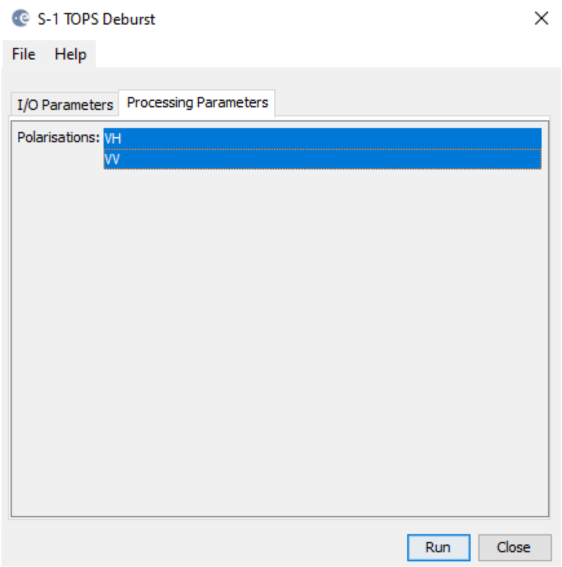
I/O Parameters:

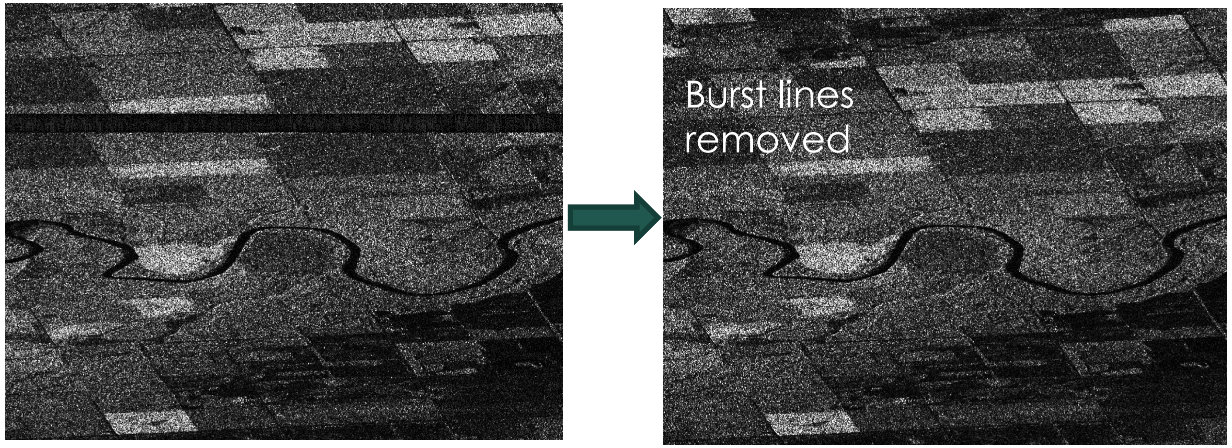
- Input: S1 Calibrated file

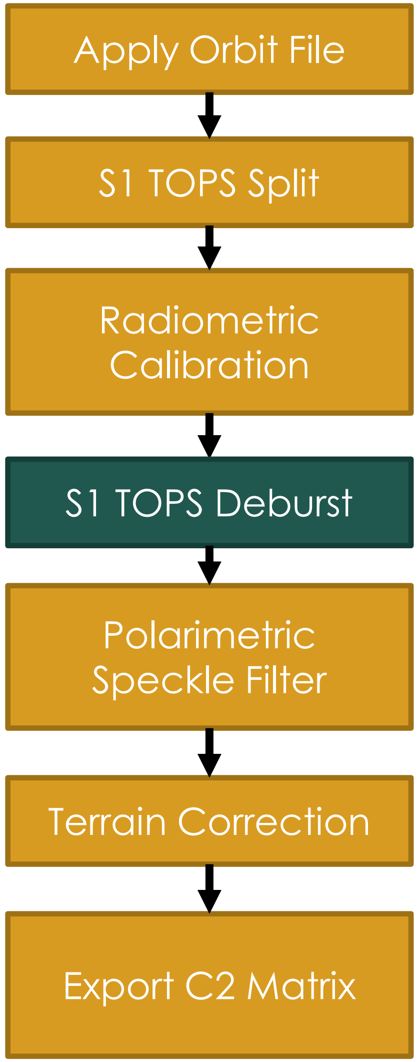
Processing Parameters:

- Select both polarizations









1. Generate C2 Matrix in SNAP

Polarimetric Speckle Filtering

Polarimetric speckle filtering to preserve phase and polarimetric information while suppressing noise. SNAP has 4 polarimetric Speckle filters (**Box Car**, IDAN, Refined Lee, Improved Lee Sigma).

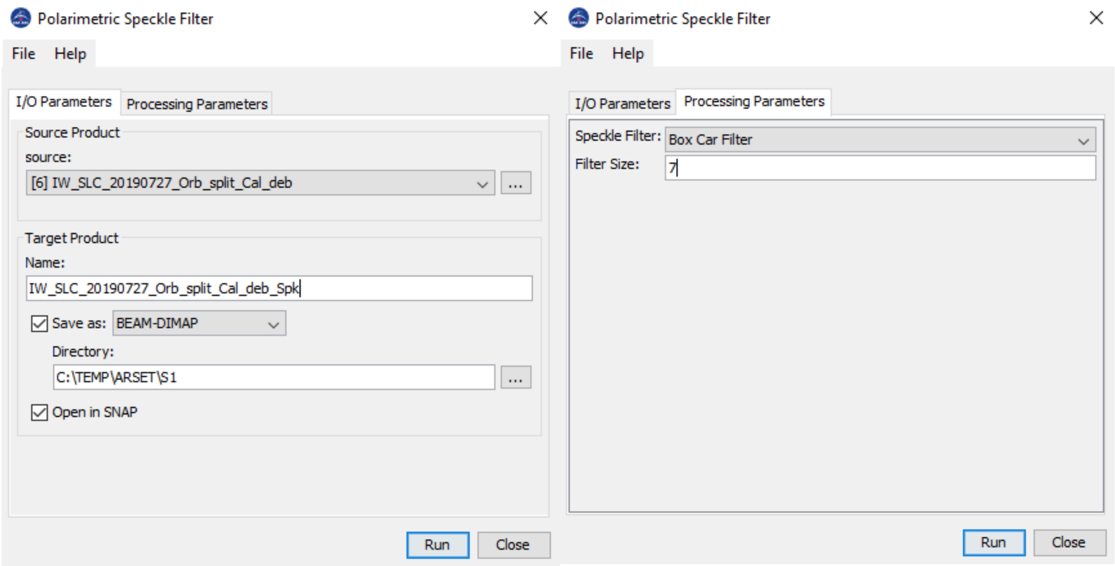
Radar → Polarimetric → Polarimetric Speckle Filter

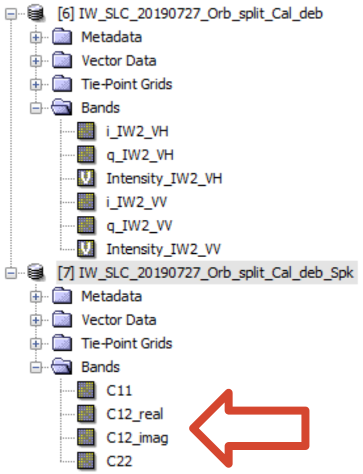
I/O Parameters:

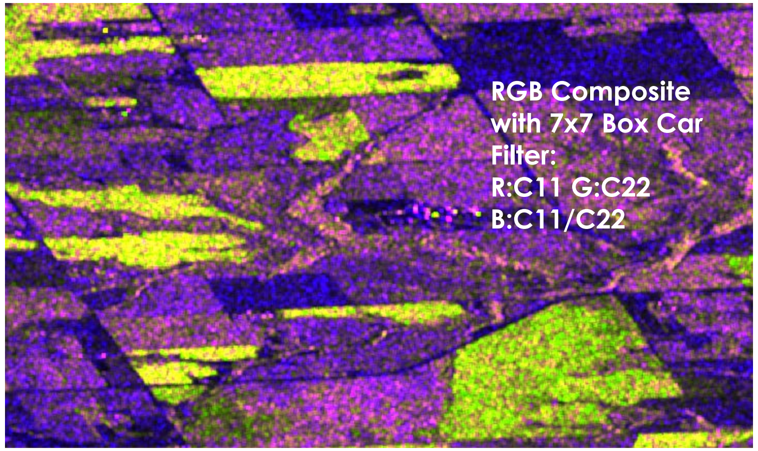
- Input: Deburst S1 Image

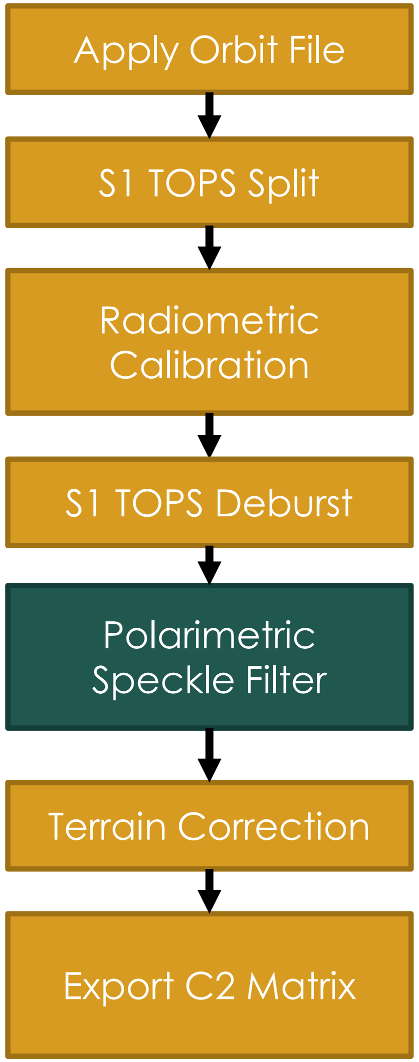
Processing Parameters:

- Box Car 7x7 filter size









1. Generate C2 Matrix in SNAP

Geometric Terrain Correction

Conversion to a coordinate system, terrain distortion correction using a DEM, and resampling from az x rn to pixel spacing (m)

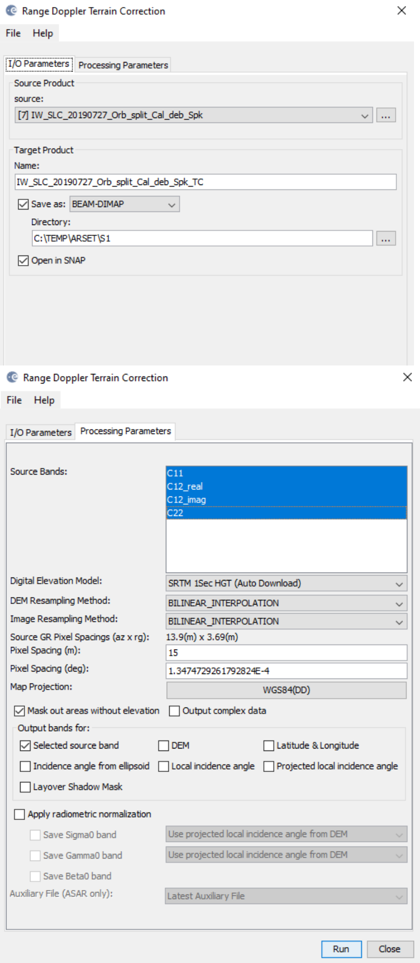
Radar → Geometric → Terrain Correction → Range-Doppler Terrain Correction

I/O Parameters:

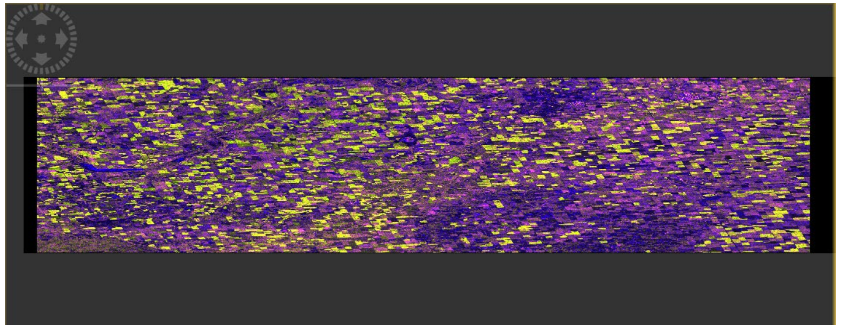
- Input: Speckle filtered image

Processing Parameters:

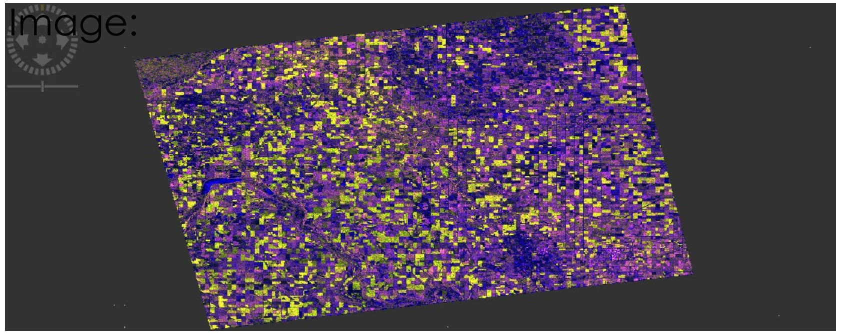
- Source Bands: select all
- DEM: SRTM 1 Sec (Auto Download)
- Resampling Method: Bilinear Interpolation

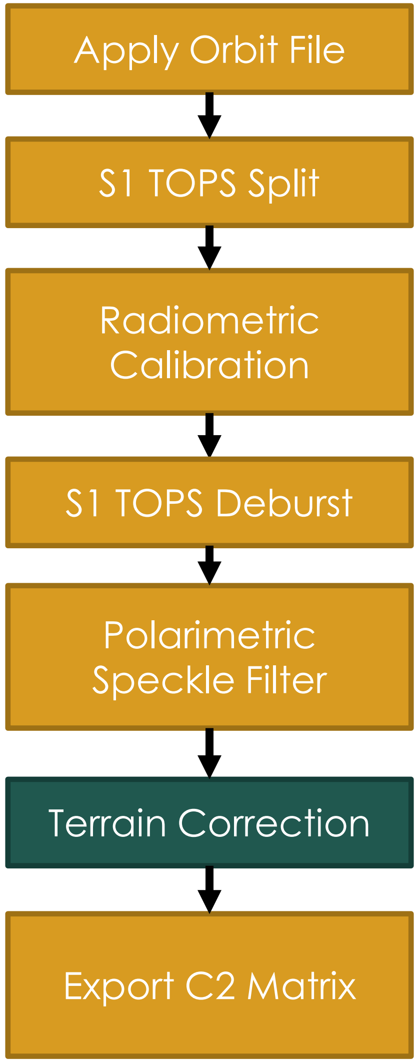


Input: Speckle Filtered Image



Output: Terrain Corrected Image:

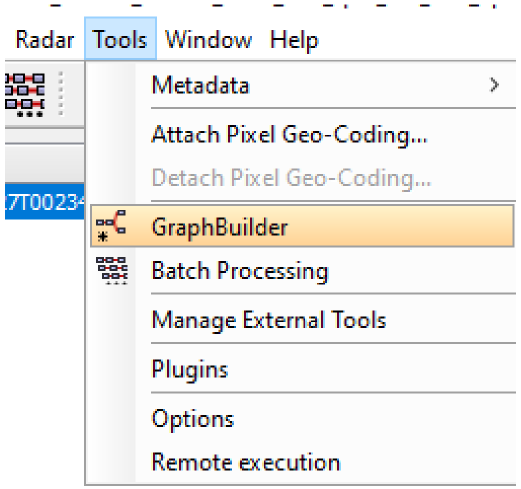


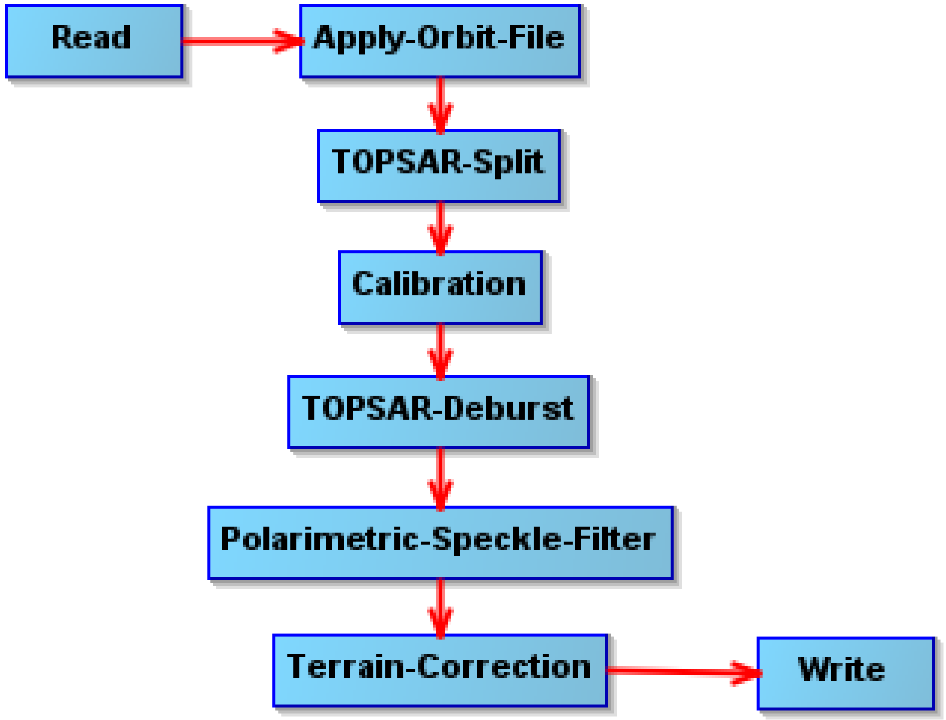


1. Generate C2 Matrix in SNAP

SNAP Graph Builder to automate workflow; useful for batch processing tasks

- Select all the processing tasks and connect in order, set appropriate I/O and Processing parameters for each tool.





1. Generate C2 Matrix in SNAP

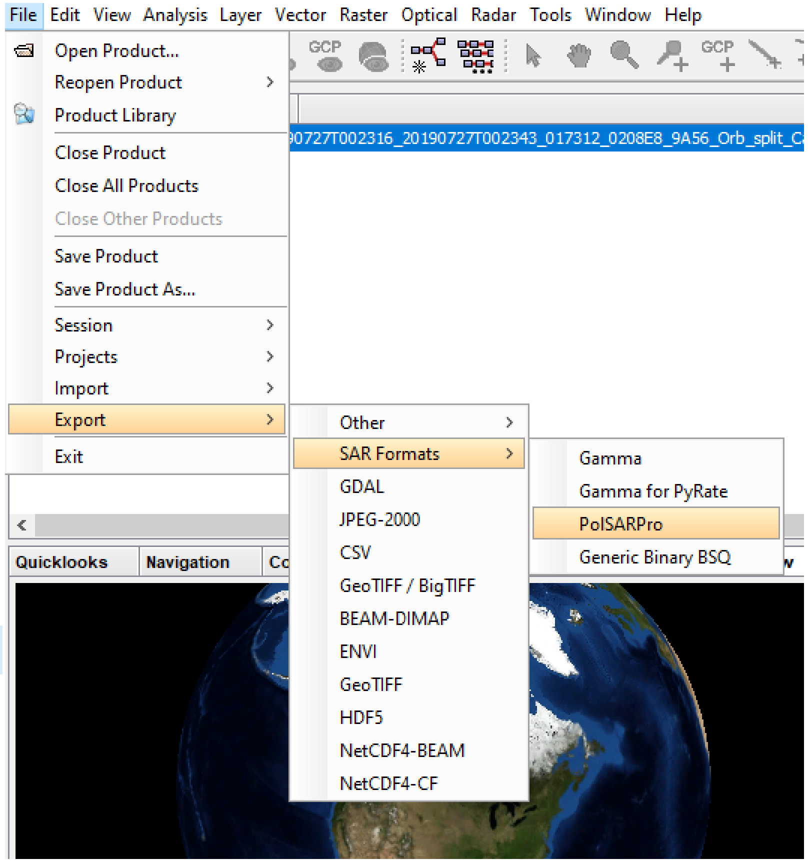
Export C2 Matrix for use in PolSARPro

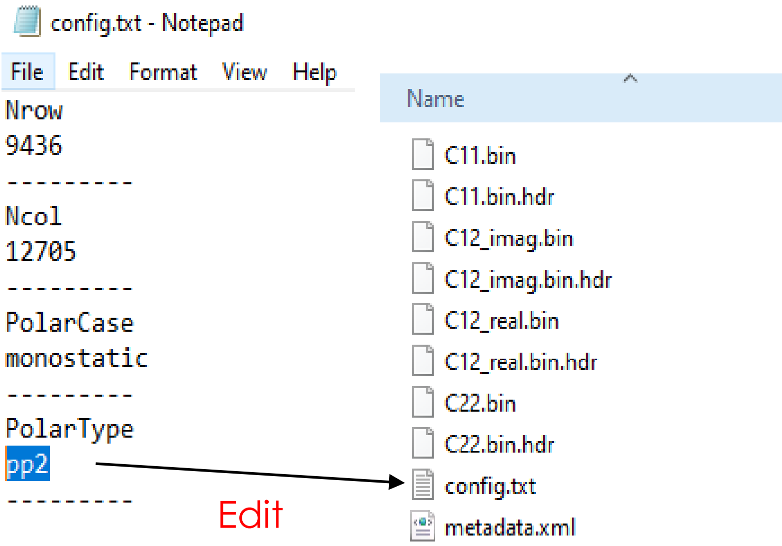
File → Export → SAR Formats → PolSARPro

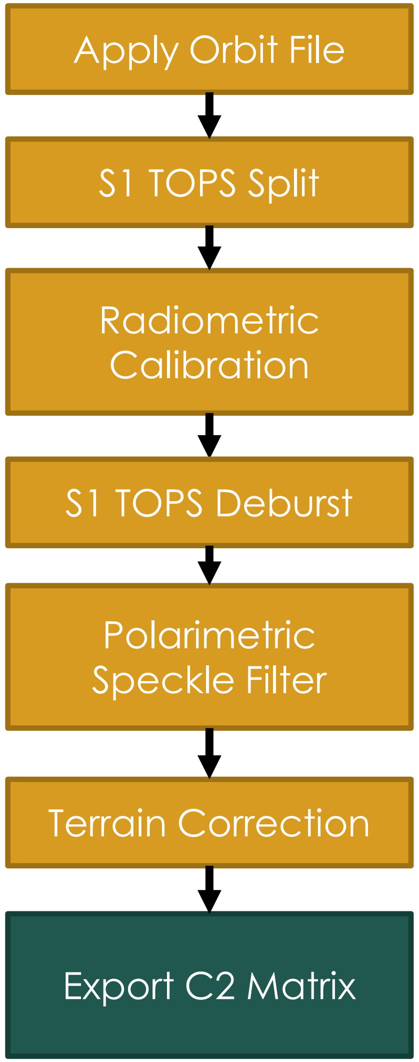
Note: Also export terrain corrected image as GeoTIFF / BigTIFF for use as georeferenced master image.

Create a folder called “C2” and save all exported PolSARPro files into it.

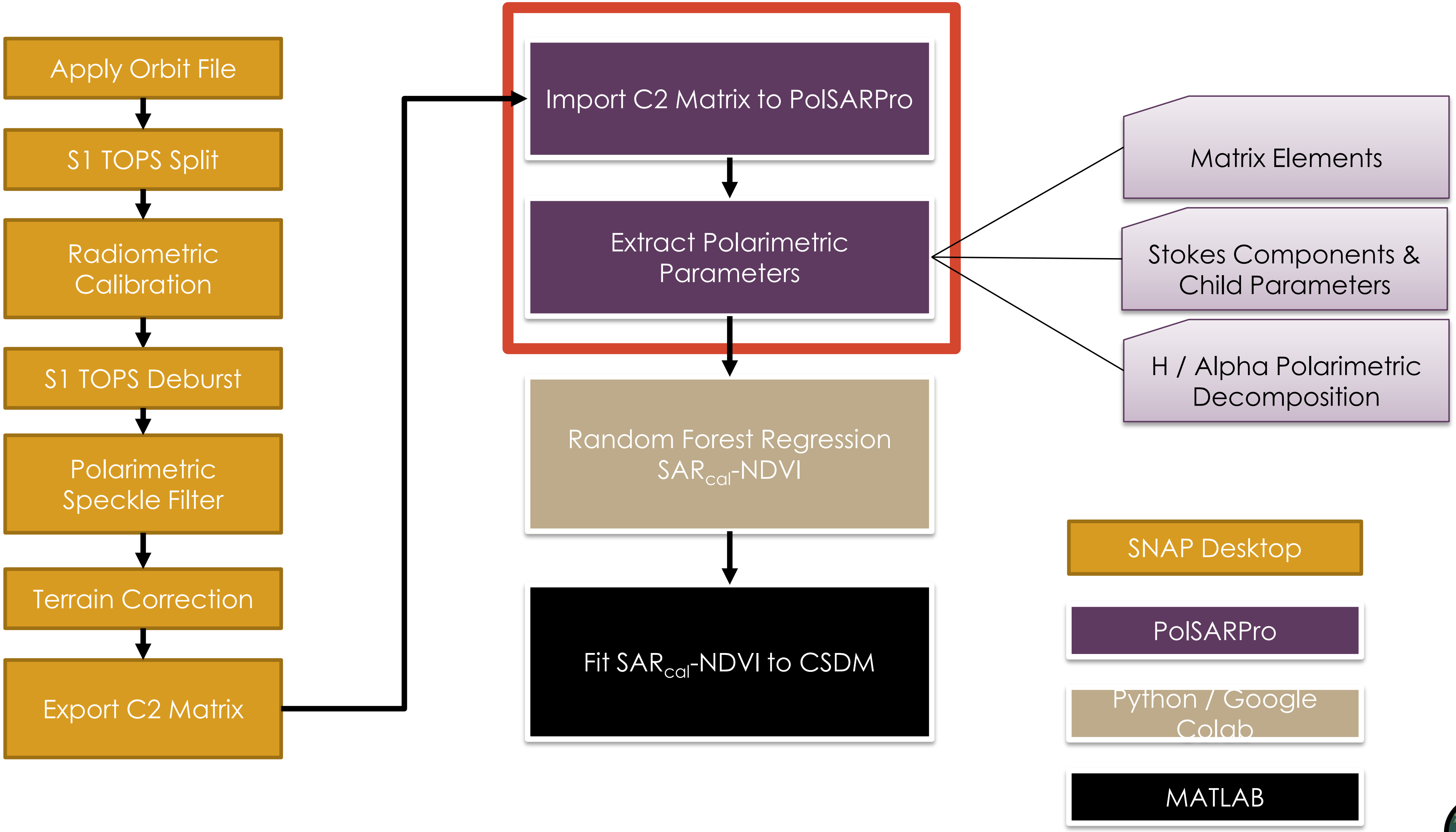
In the new exported C2 folder, change config.txt “PolarType” from “dual” to “pp2” using notepad. This allows PolSARPro to recognize the data as a 2x2 matrix. Save.







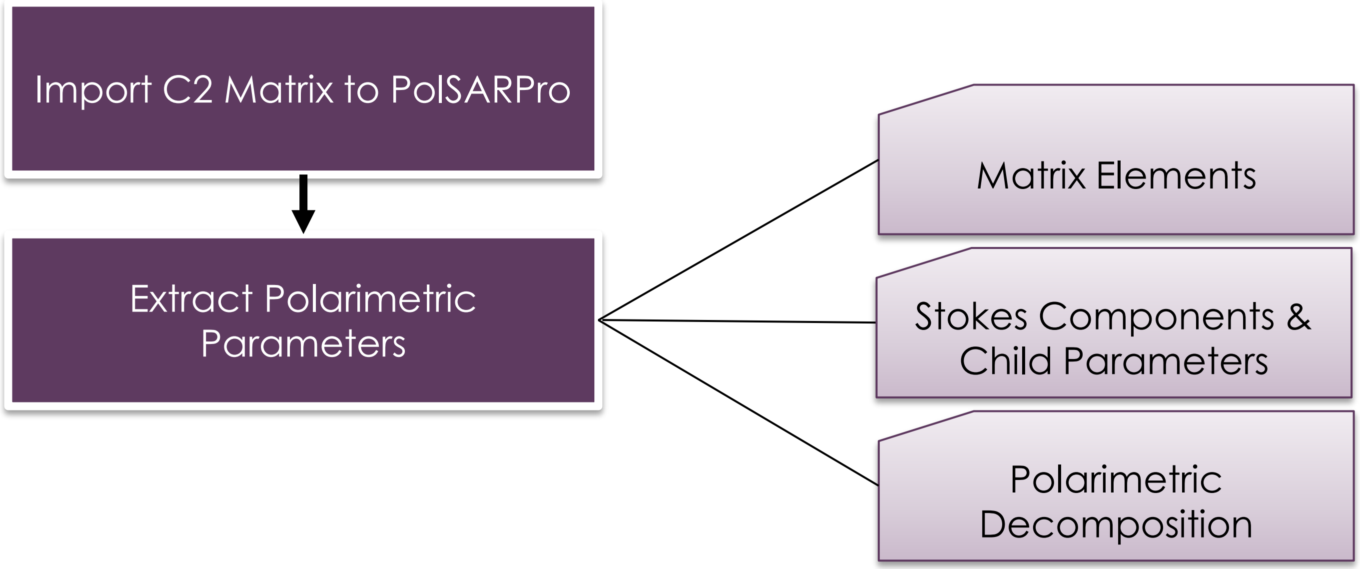
Processing Methodology



2. Extract Polarimetric Features: PolSARpro

Download PolSARpro & dependencies; be sure to follow installation instructions carefully.

https://step.esa.int/main/download/polsarpro-v6-0-biomass-edition-toolbox-download/



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POLSARPRO V6.0.3 (BIOMASS EDITION)

WIN64 INSTALLATION PROCEDURE

UNIVERSITÉ DE RENNES 1

IETR

1 - PRE - INSTALLATION

PolSARpro v6.0.3 (Biomass Edition) Software requires the installation of the following packages (*if not already installed on the machine*) :

Tcl (*Tool Command Language*) - **Tk** (*ToolKit*) enable the execution of powerful **GUIs** (*Graphical User Interface*). **Tcl-Tk** binary distribution and installers for Windows platform are available for download from :

https://www.magicsplat.com/tcl-installer/index.html

Gimp (*GNU Image Manipulation Program*) is a free and open-source graphics editor. The current stable release of **Gimp** for Windows platform is available for download from :

https://www.gimp.org/downloads/

ImageMagick is a free and open-source software suite for converting / creating / editing image files. The current stable release of **ImageMagick** for Windows platform is available for download from :

https://www.imagemagick.org/script/download.php#windows

SNAP (*Sentinel Application Platform*) reunites all Sentinel Toolboxes in order to offer the most complex platform for this mission. The current stable release of **SNAP** for Windows platform is available for download from :

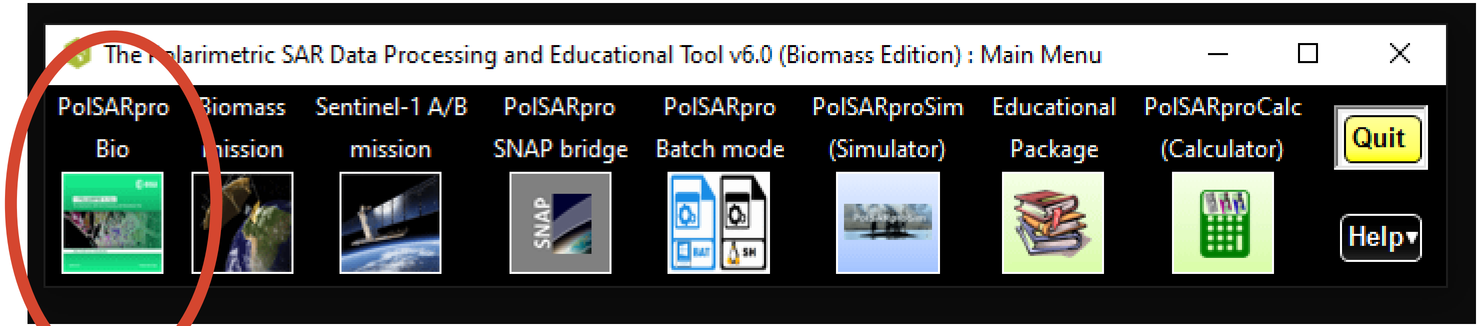
http://step.esa.int/main/download/

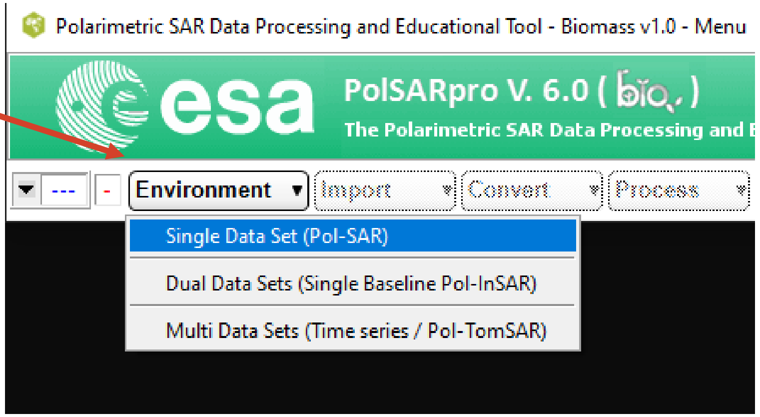
PolSARpro: Set up Environment

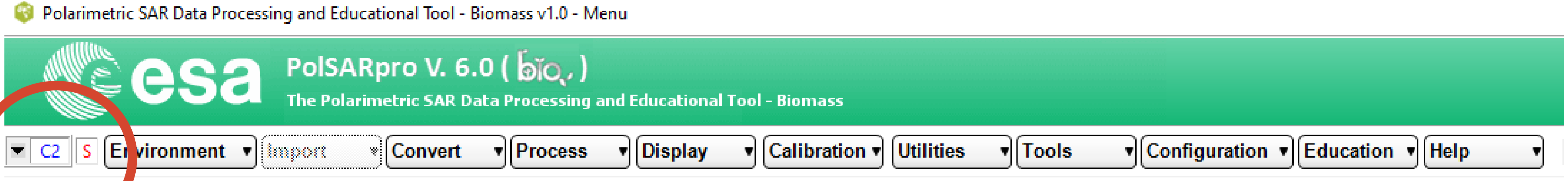
Open PolSARpro Bio

Environment → Single Data Set → Navigate to folder containing C2 Folder

Bottom left should read as C2







PolSARpro: Process C2 Matrix Elements

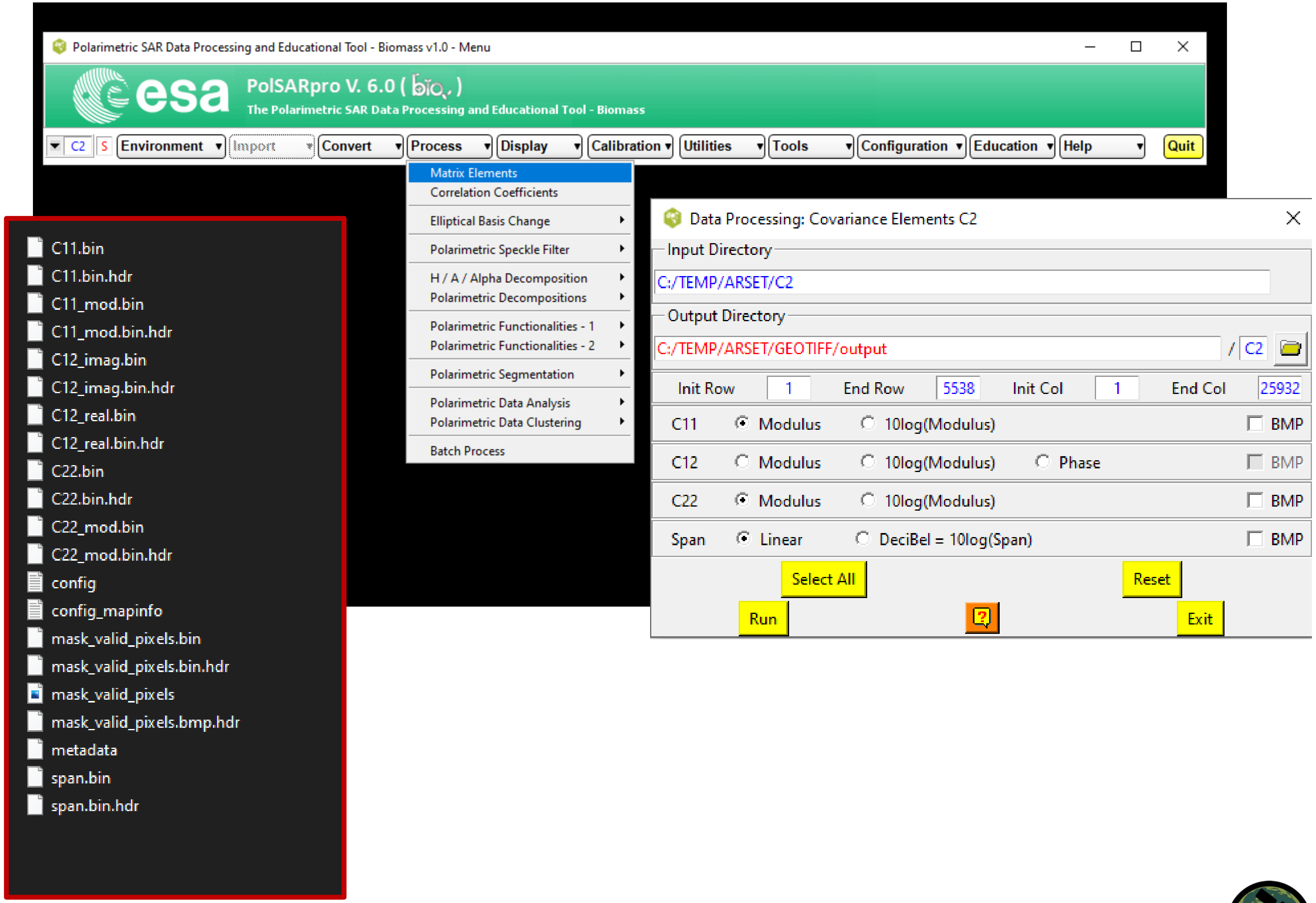
Data Processing Covariance Elements [C2]

Process → Matrix Elements

- Select I/O directories, create output folder for new parameters
- Select C11 Modulus, C22 Modulus, and Span Linear

Modulus: linear representation of [C2] amplitude

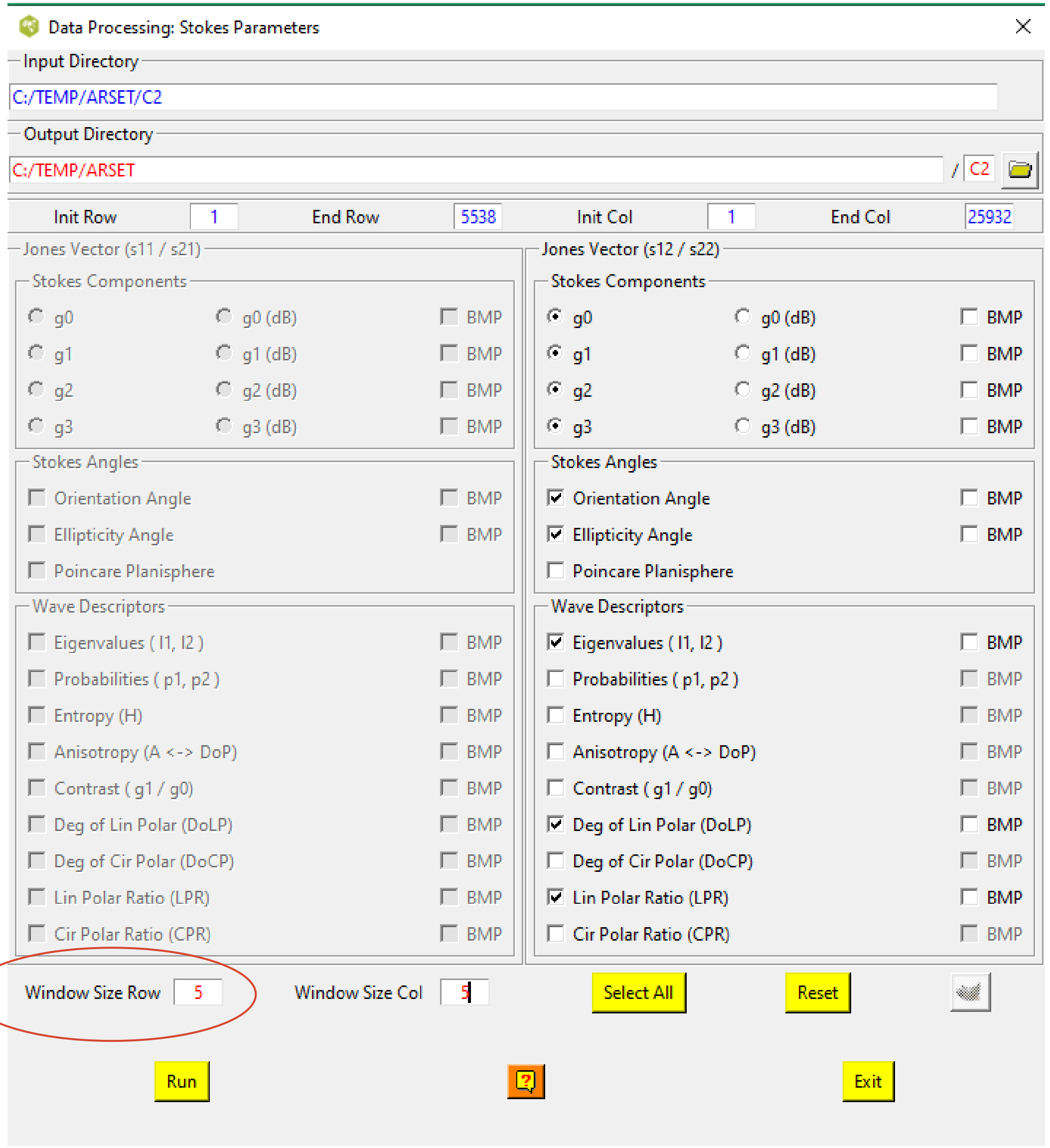
Span: total power (intensity), sum of all matrix elements



PolSARpro: Generate Stokes Parameters

Process → Polarimetric Functionalities – 1 → Stokes Parameters

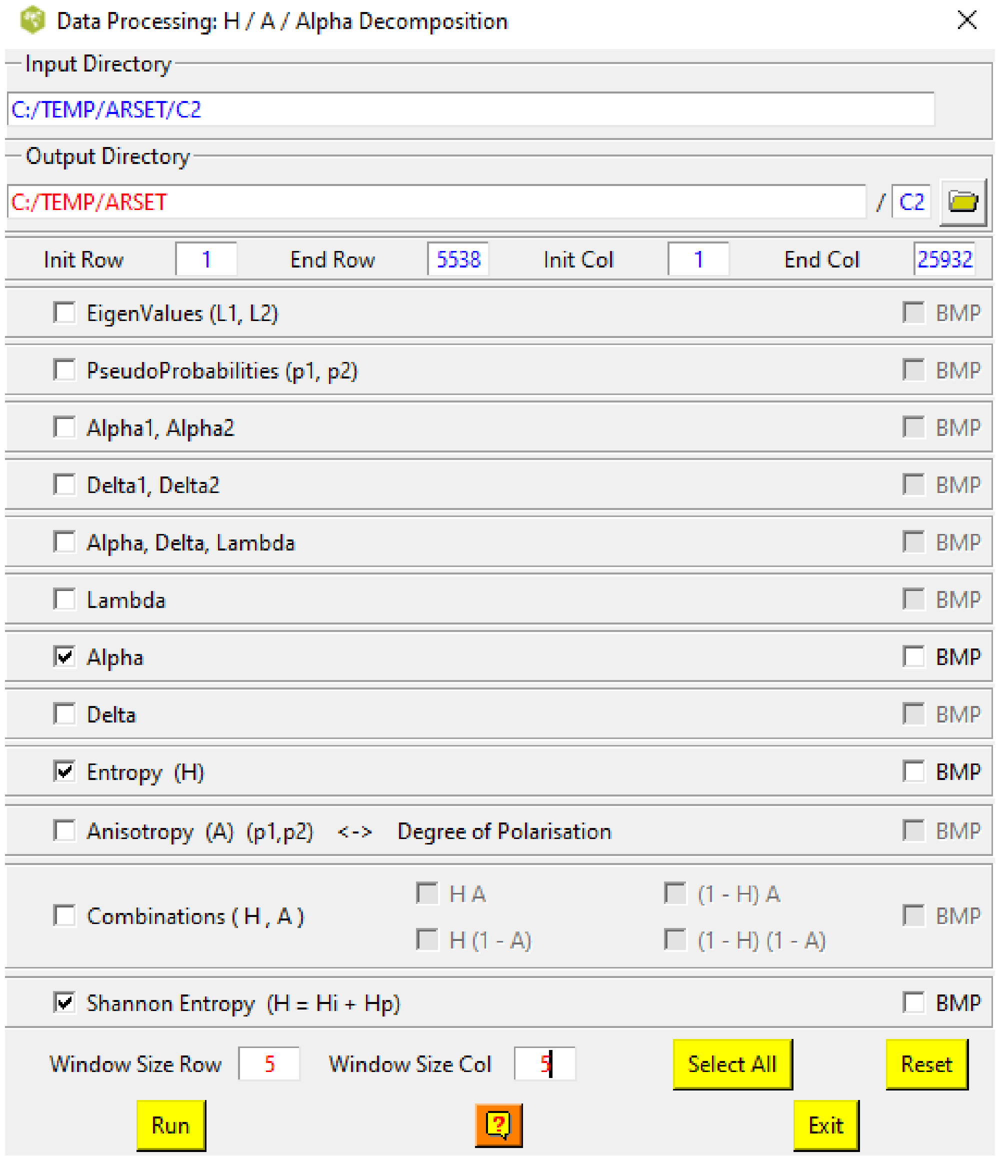
- Select I/O directories (C2 folder)
- Choose parameters to generate:
  - Stokes parameters (S_0, S_1, S_2, S_3)
  - Orientation (Ψ) and ellipticity angle (Χ)
  - Degree of polarization (DoP), Degree of linear polarization (DoLP), linear polarization ratio (LPR)
  - Eigenvalues (l_1 & l_2)
- Set processing **window size** (ex. 3x3, 5x5)



PolSARpro: Generate H / Alpha Decomposition Parameters

Process → H / A /Alpha Decomposition → Decomposition Parameters

- Choose appropriate I/O directories
- Select parameters to generate
  - Alpha, Entropy (H), Shannon Entropy (SE)
- Set processing window size (ex. 3x3, 5x5)



Python: Convert PolSARpro output to GeoTIFF (Python)

Script: Convert_PolSARpro_Output_to_Tif.py

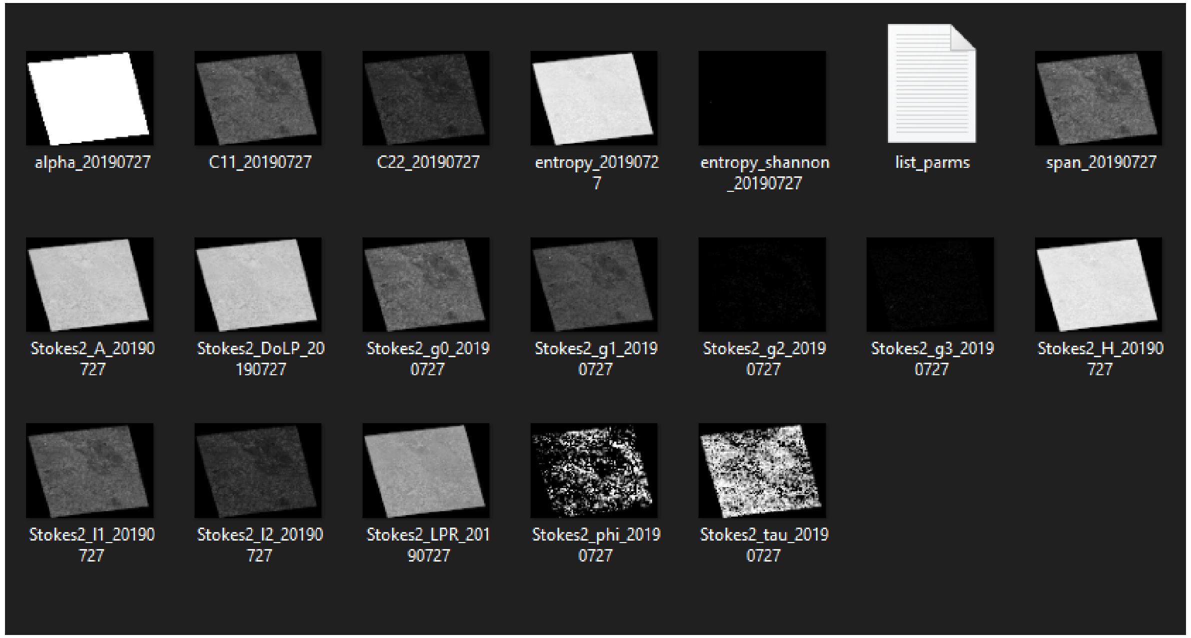
Dependencies: Python 3.6 or greater, **GDAL**

Files required:

- PolSARPro Output (C2 Folder)
- MasterTIF: Exported Terrain Corrected GeoTIFF file from final SNAP processing step
- *ListParms.txt*: a list of the parameters in the C2 folder to convert to GeoTIFF

Change Parameters:

- Change inpath/outpath parameters at the bottom of the script to location of input C2 folder and location to save .tif files for Output.
- Change location of MasterTIF file for georeferencing.



Random Forest Regression in Python

- Required **Carman_Corn.csv** file derived from the reference dataset of 946 sub field objects (ID_corn) and S1 parameters (X) and S2 NDVI data (Y)
- Polygon layer of reference sub-field location (Corn)
  - For OBIA Segmentation; use optical data, i.e. single date or seasonal composite of corresponding S2 imagery.
  - Multiresolution Image segmentation of seven S2 NDVI images for 2019 growing season.
- Feature Extraction of mean NDVI (S2); mean of all S1 quasi-polarimetric parameters, saved to .CSV

```python
# Import and print the dataset - connect to google drive

data = pd.read_csv('/content/drive/MyDrive/ARSET_Demo/Carmen_Corn.csv')
print(data)
list(data.columns)
```

```
     S2_NDVI_Corn  C11_Corn  C22_Corn  Span_Corn  g0_Corn  g1_Corn  g2_Corn  \
0        0.653550        61        17         79       81       45        1
1        0.539260        54        13         67       69       42        2
2        0.538964        70        15         86       88       57        0
3        0.559707        64        14         79       80       51        0
4        0.492806        51        12         64       65       40        0
..            ...       ...       ...        ...      ...      ...      ...
942      0.815112        63        16         79       82       49        1
943      0.892819       124        27        151      154       99       -4
944      0.896989        80        19         99      101       61       -1
945      0.857591        81        19        100      101       62       -1
946      0.778980        39        11         51       51       29        0

     g3_Corn  DoLP_Corn  Lpr_Corn  l1_Corn  l2_Corn  Phi_Corn  Tau_Corn  \
0         -1        575       276       64       17       924      -317
1         -2        622       238       56       13      1706     -1016
2         -1        657       210       73       15       -52      -392
3         -2        640       223       66       14       225     -1315
4         -1        620       240       53       12       222      -830
..       ...        ...       ...      ...      ...       ...       ...
942        0        609       249       66       16       489      -203
943       -3        653       215      128       26     -1168      -891
944        1        624       236       82       19      -688       522
945        0        621       237       82       19      -421      -139
946        0        578       272       40       11      -181       249

     entropy_Corn  alpha_Corn  DoP_Corn  entropy_sh_norm_Corn
0             743       21947       578                   592
1             692       19859       629                   461
2             657       18164       661                   591
3             671       19184       648                   545
4             695       20062       626                   427
..            ...         ...       ...                   ...
942           708       20421       614                   567
943           659       18637       659                   845
944           693       19775       628                   665
945           695       19643       626                   664
946           737       21901       584                   360
```

Python: Random Forest Regression

SAR_{cal}-NDVI

Random Forest Regression; Scikit-learn for Random Forest Regression (RFR) as RandomForestRegressor

Dependencies: Carman Corn Dataset

- S1 Variables and S2 NDVI extracted mean at the field-object level
- 17 Sentinel-1 variables for all S1 image dates
- Corresponding S2 NDVI within 2-3 days of S1 acquisition

```
[8]  import pandas as pd
     # Read in data
     data = pd.read_csv('/content/drive/MyDrive/ARSET_Demo/Carmen_Corn.csv')
     # Descriptive statistics for each column
     data.describe()
```

	ID_Corn	days_5days	S2_NDVI_Corn	C11_Corn	C22_Corn	Span_Corn	g0_Corn	g1_Corn	g2_Corn	g3_Corn
count	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000
mean	659.965153	762.569166	0.773468	90.014784	19.903907	110.926082	113.578669	71.979937	-0.856389	0.908131
std	76.711148	50.812221	0.174372	27.671850	5.947289	33.551400	34.265363	22.779730	1.776779	1.785248
min	522.000000	703.000000	0.231820	30.000000	7.000000	37.000000	39.000000	23.000000	-7.000000	-5.000000
25%	594.000000	715.000000	0.737702	68.000000	16.000000	84.000000	86.000000	55.000000	-2.000000	0.000000
50%	663.000000	727.000000	0.855291	90.000000	20.000000	111.000000	115.000000	71.000000	-1.000000	1.000000
75%	724.000000	808.000000	0.886698	108.000000	23.000000	132.000000	134.500000	86.500000	0.000000	2.000000
max	793.000000	820.000000	0.939080	184.000000	45.000000	232.000000	235.000000	142.000000	6.000000	10.000000

	DoLP_Corn	Lpr_Corn	l1_Corn	l2_Corn	Phi_Corn	Tau_Corn	entropy_Corn	alpha_Corn	DoP_Corn	entropy_sh_norm_Corn
count	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000	947.000000
mean	640.949314	223.414995	93.379092	19.856389	-326.027455	334.175290	671.074974	18963.592397	646.492080	590.124604
std	35.737260	27.676780	28.595171	5.909149	679.750832	659.253471	38.550119	1704.447310	35.048331	125.210855
min	487.000000	136.000000	31.000000	7.000000	-2270.000000	-1506.000000	515.000000	13348.000000	494.000000	116.000000
25%	620.000000	204.500000	70.000000	16.000000	-786.000000	-115.500000	645.000000	17819.500000	626.000000	509.500000
50%	642.000000	222.000000	93.000000	20.000000	-328.000000	307.000000	671.000000	18885.000000	648.000000	595.000000
75%	665.000000	239.000000	111.500000	23.000000	115.000000	758.500000	694.500000	19941.000000	670.500000	682.500000
max	767.000000	355.000000	190.000000	45.000000	1728.000000	2787.000000	816.000000	26207.000000	770.000000	937.000000

RFR Python Demo

https://colab.research.google.com/drive/1TOlrpDpzg95OtZVD4NI85k0zX7pgwTga?usp=sharing

Python: Random Forest Regression

RFR Python Demo
https://colab.research.google.com/drive/1TOlrpDpzg95OtZVD4NI85k0zX7pgwTga?usp=sharing

1. Import Packages, and QC dataset for missing values

```
[23] import pandas as pd
     import numpy as np
     # Read in data
     data = pd.read_csv('/content/drive/MyDrive/ARSET_Demo/Carmen_Corn.csv')
     # print descriptive statistics for each column
     data.describe()
```

2. Convert data to Arrays

```
[13] Y = np.array(data['S2_NDVI_Corn'])
     X = data.drop('S2_NDVI_Corn', axis = 1)
     data_list = list(data.columns)
     print(data_list)
     X = np.array(X)
```

Python: Random Forest Regression

3. Use SciKit-learn to split data into test (70%) and training sets (30%)

```
[4] from sklearn.model_selection import train_test_split
    # Split the data into training and testing sets, random state set to retain results
    train_features, test_features, train_labels, test_labels = train_test_split(X, Y, test_size = 0.30, random_state = 0)
```

4. Run RF Regression Model (nTree = 500)

```
[24] from sklearn.ensemble import RandomForestRegressor
     # Run the RFR with 500 trees
     rf = RandomForestRegressor(n_estimators = 500, random_state = 0)
     # train the model on training data
     rf.fit(train_features, train_labels);
```

5. Predict the model on the test data, calculate accuracy and absolute mean error

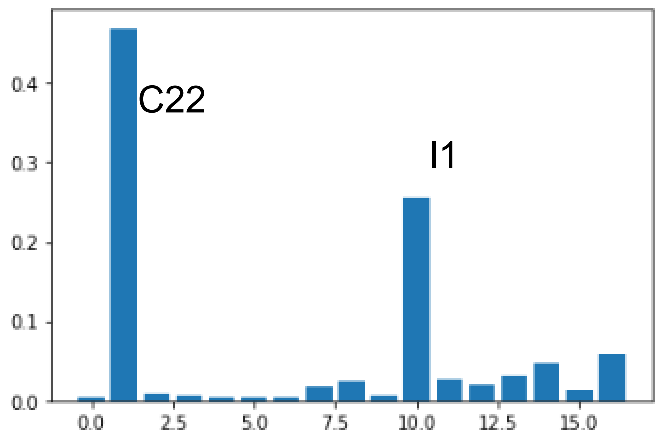
```
[10] predictions = rf.predict(test_features)
     errors = abs(predictions - test_labels)
     print('Mean Absolute Error:', round(np.mean(errors), 2),'degrees.')
     accuacy = 100 * (errors / test_labels)
     mape = 100 * (errors / test_labels)
     accuracy = 100 - np.mean(mape)
     print('Accuracy:', round(accuracy, 2), '%.')

     Mean Absolute Error: 0.04 degrees.
     Accuracy: 93.39 %.
```

Python: Random Forest Regression

- **Optional**: Investigate feature importance, and implement variable selection method to improve model accuracy.

```
from matplotlib import pyplot
# get importance from rfr model
importance = rf.feature_importances_
# summarize feature importance
for i,v in enumerate(importance):
 print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score: 0.00469
Feature: 1, Score: 0.46914
Feature: 2, Score: 0.00849
Feature: 3, Score: 0.00646
Feature: 4, Score: 0.00501
Feature: 5, Score: 0.00388
Feature: 6, Score: 0.00303
Feature: 7, Score: 0.01677
Feature: 8, Score: 0.02419
Feature: 9, Score: 0.00529
Feature: 10, Score: 0.25635
Feature: 11, Score: 0.02658
Feature: 12, Score: 0.01927
Feature: 13, Score: 0.03109
Feature: 14, Score: 0.04772
Feature: 15, Score: 0.01346
Feature: 16, Score: 0.05859
```



RFR feature importance plot

RFR feature importance scores

SARcal-NDVI to CSDM

A Crop Structure Dynamics Model (CSDM) is then used to fit the SAR_{cal}-NDVI estimates to create a daily (GDD) time step of crop condition.

$$D = D_{max}\left[\frac{1}{1+e^{-b(T-T_i)}} - e^{-a(T-T_S)}\right]$$

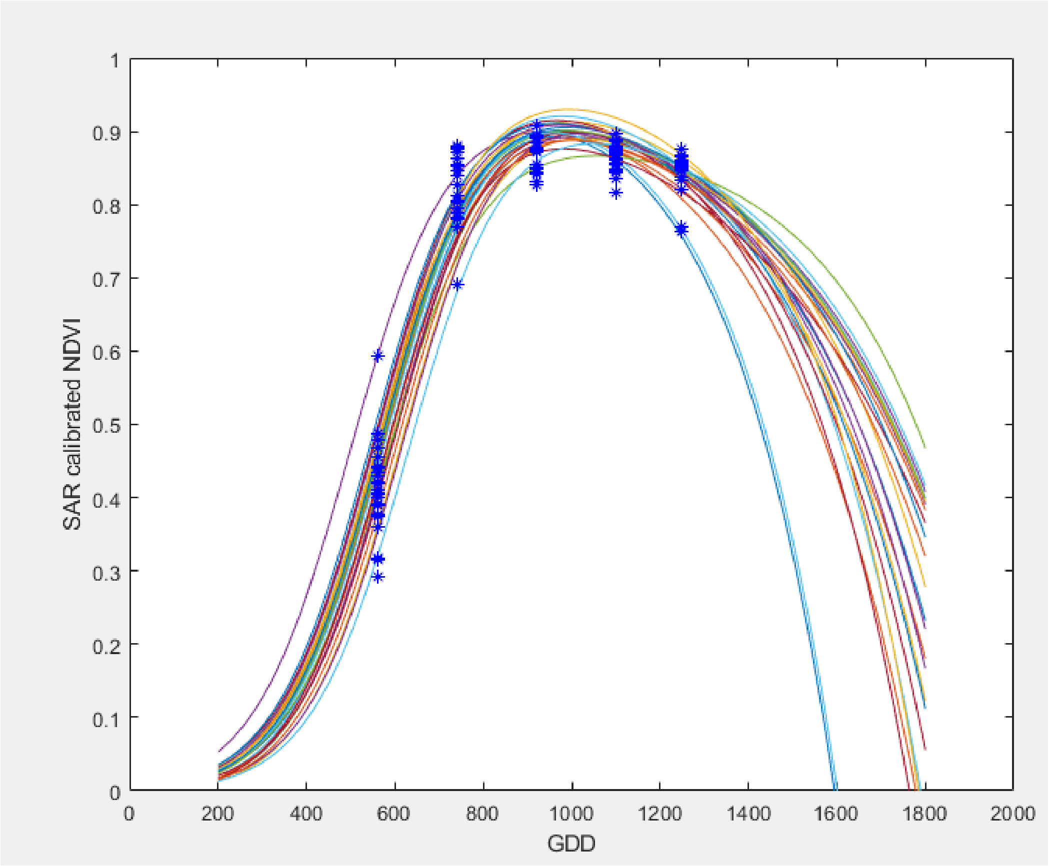
D: canopy structural descriptor with a maximum achievable value D_{max} . D is set as SAR_{cal}-NDVI

T: the accumulative Growing Degree Days (GDD) (for Canada, set to May 1)

The model describes the canopy structure in two parts: growth and senescence.

The growth period is defined by a logistic equation with parameters b and T_i. The coefficient b is the relative growth rate at the inflection point T_i.

The senescence is defined by an exponential equation with parameter a and T_s. a is the senescence rate. T_s represents the accumulative GDD at which D decreases to 0 due to senescence.



Lines: CSDM fit for each sub-field object (Jiao et al., 2022)

References

PolSARpro v6.0 (Biomass Edition), https://www.ietr.fr/polsarpro-bio/

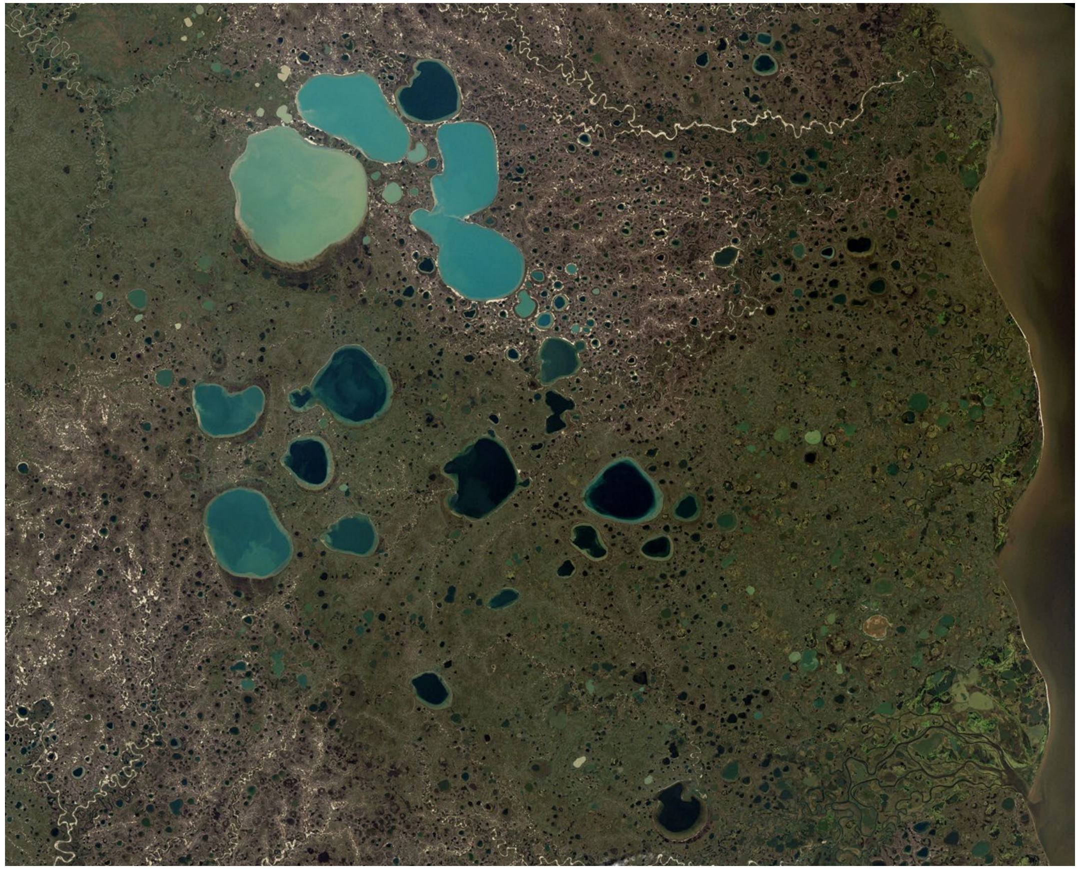
Scikit-learn: Machine Learning in Python, Pedregosa *et al.*, JMLR 12, pp. 2825-2830, 2011.

SNAP - ESA Sentinel Application Platform v8.0.0, *http://step.esa.int*

Xianfeng Jiao, Heather McNairn, Bahareh Yekkehkhany, Laura Dingle Robertson & Samuel Ihuoma (2022) Integrating Sentinel-1 SAR and Sentinel-2 optical imagery with a crop structure dynamics model to track crop condition, International Journal of Remote Sensing, 43:17, 6509-6537, DOI: 10.1080/01431161.2022.2142077

Questions?

- Please enter your questions in the Q&A box. We will answer them in the order they were received.
- We will post the Q&A to the training website following the conclusion of the webinar.



https://earthobservatory.nasa.gov/images/6034/pothole-lakes-in-siberia

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  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-crop-mapping-using-synthetic-aperture-radar-sar-and-optical-0
- ARSET Website:
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Thank You!