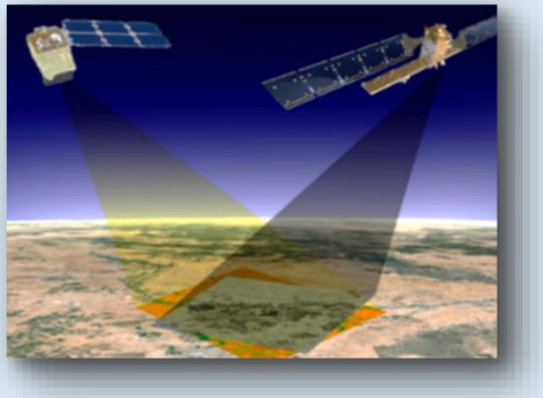
הנדסת מערכות תוכנה ומידע
Software and Information
Systems Engineering

The Remote Sensing Labratory
Jacob Blaustein Institutes for Desert Research
Ben-Gurion University of the Negev

Mining Seasonal Patterns in Earth Observations

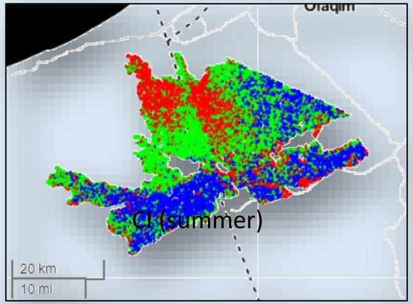


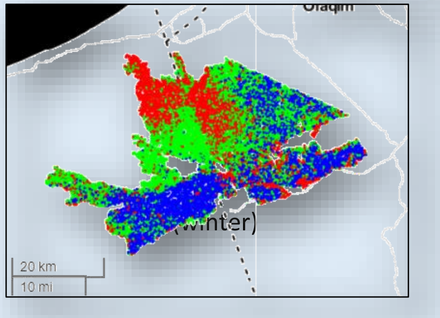
*** Thesis Final Exam Presentation ***

By:
Ricky Shama

Under the Supervision of:
Prof. Mark Last
Prof. Arnon Karnieli

14.6.22





Agenda

- Introduction
- Background
- Research Definition
- Methodology
- Implementation
- Results
- Conclusions

- EO (earth observations) are the **main** resource used for monitoring and understanding climate changes.

- They are considered as **Big Data** (Volume, Velocity, Variety).

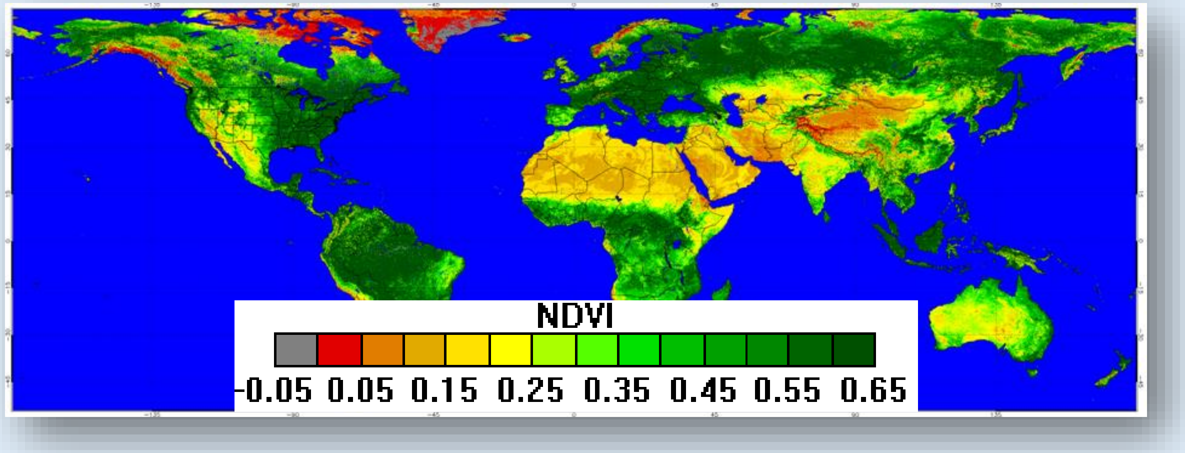
- **GEE** (Google Earth Engine): analytical platform.

- **Periodicity/ Seasonality Detection**: periodic pattern mining in time-series data. Finding periodic behaviors is useful in other time-series tasks, including: forecasting, clustering, etc.

➔ In this research I developed a seasonality detection model (using GEE, machine-learning) in earth observations;

Case Study Area: *The Israeli-Egyptian Sandfield* (unique seasonal optical dynamics, human activities vs. nature conservation).

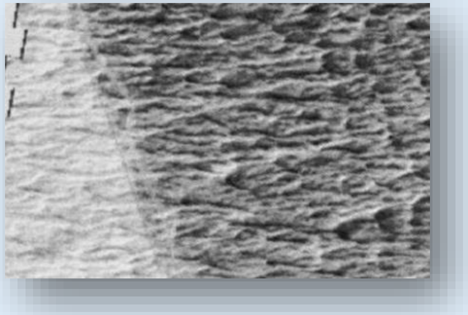
- **Remote Sensing (RS) Index:** a numerical indicator which is achieved using a mathematical formula applied on various **spectral bands** of an image per **pixel**. The **level** of the index indicates a rate of a cover (e.g vegetation), content, etc.
- RS indices used in this research: **CI** (Crust Index), **LST** (Land Surface Temperature), **NDVI /NDWI** (Normalized Difference Vegetation/ Water Index), **precipitation**, **RADAR** backscatter coefficient.



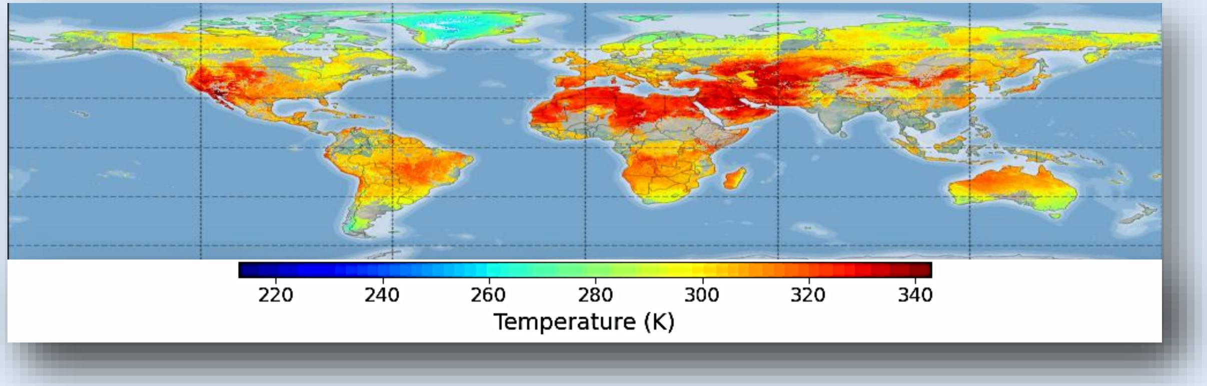
Examples:

- **CI** – (Biological) **C**rust **I**ndex. Soil crust contain cyanobacteria, mosses, algae, etc. that are essential components of arid and semi-arid eco-systems. There is a unique feature of the pigment found in soil crusts, resulting in a relatively higher reflectance in the **blue** spectral region compared to soil without cyanobacteria. A **higher** value of CI indicates a higher content of cyanobacteria in the soil.

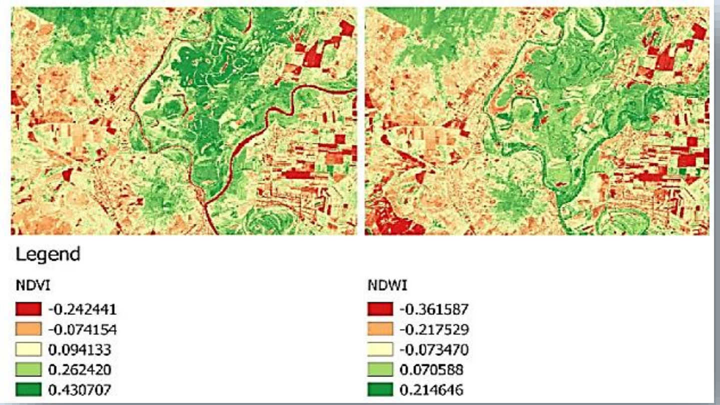
$$CI = 1 - \frac{RED - BLUE}{RED + BLUE}$$



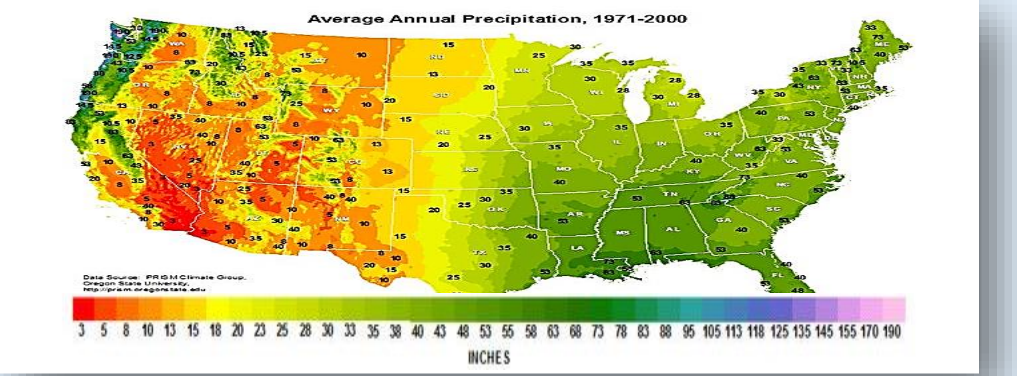
- **LST** – **L**and **S**urface **T**emperature. It is estimated by the **Infra-Red** spectral channels of the satellites’ sensors. It depends on the **albedo** (fraction of light that is reflected by a body or surface), the vegetation cover and soil moisture. They all respond rapidly to changes in solar radiation due to cloud cover, aerosol concentration, and daily variations of illumination, which affect the LST, too.



- **NDVI** – **N**ormalized **D**ifference **V**egetation **I**ndex. Useful for vegetation monitoring. It describes the difference between visible and near-infrared reflectance of **vegetation cover**, thus, it can be used to estimate the **density of green** on an area of land. $$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+\mathrm{RED}}$$
- **NDWI** – **N**ormalized **D**ifference **W**ater **I**ndex. Reflects moisture content in plants and soil. $$\mathrm{NDWI} = \frac{\mathrm{NIR}-\mathrm{SWIR}}{\mathrm{NIR}+\mathrm{SWIR}}$$



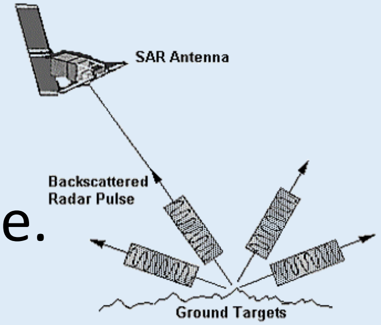
- **Precipitation** – Any liquid or frozen water that forms in the atmosphere and falls back to the Earth. It comes in many forms, like: rain, hail, snow. Along with evaporation and condensation, precipitation is one of the three major parts of the global water cycle. Can be measured either by ground-based instruments, or satellites' sensors which estimate the electro-magnetic radiation as reflected from the top of the clouds, rain droplets.


Average Annual Precipitation, 1971-2000

Data Source: PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu

- **RADAR** Backscatter Coefficient – The portion of the outgoing radar signal that the target redirects directly back towards the radar antenna. In general, it is computed as the **ratio** between the **received** energy by the sensor, to the **transmitted** energy by the source. Usually measured in [dB].

→ Example of polarization mode: VH – **V**ertical Transmit-**H**orizontal Receive.

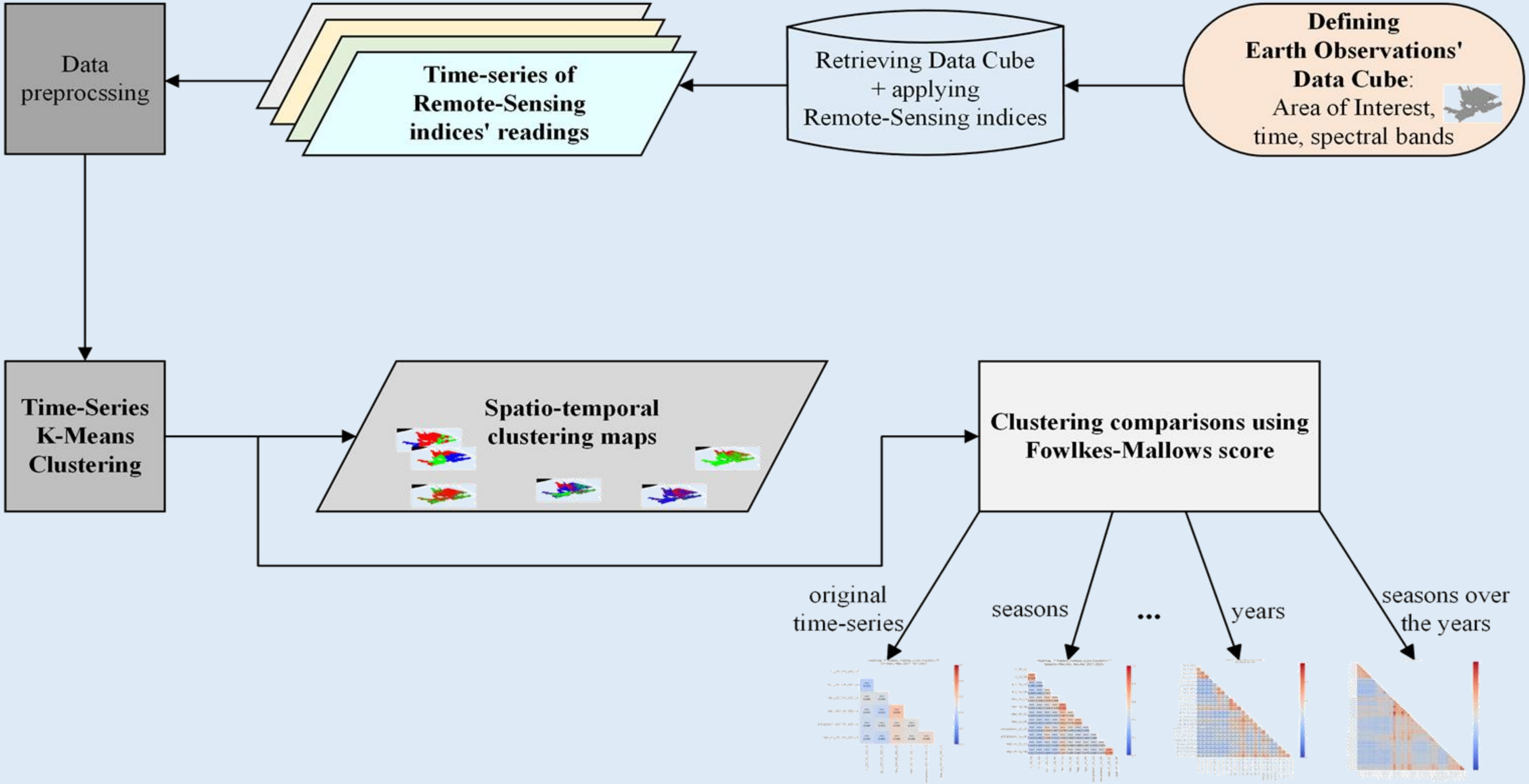


→ SAR **– S**ynthetic **A**perture **R**adar. A form of radar system that is used to create 2D/3D reconstructions of objects, such as landscapes, independent of weather, and solar radiation. The applications include **topography**, geology mapping.

- **Research Goal**: evaluating the similarities between:
  - ***Different*** time intervals' **clusterings**, of the ***same*** RS index.
  - ***Same*** time intervals' **clusterings**, of ***different*** RS indices.
  - ***Different*** time intervals' **clusterings**, of ***different*** RS indices.
- **Motivation**: areas representing natural and anthropogenic land transformation, require monitoring, understanding the changes, and responding to them.

- **Current limitations:** Existing studies mainly deal with EO data related to a **limited** number of RS indices (~1-4), with low frequency time-series analysis (e.g. yearly, monthly sampling).

- **Contribution**: This research suggests a seasonality detection model which is based on data related to **multiple** RS indices (6), which together cover a **wide** range of the electromagnetic spectrum, with **high** frequency time-series analysis (daily/ weekly sampling), in order to capture the subtle optical changes/ anomalies in time.



Data preprocssing

Time-series of Remote-Sensing indices' readings

Retrieving Data Cube + applying Remote-Sensing indices

Defining Earth Observations' Data Cube: Area of Interest, time, spectral bands

Time-Series K-Means Clustering

Spatio-temporal clustering maps

Clustering comparisons using Fowlkes-Mallows score

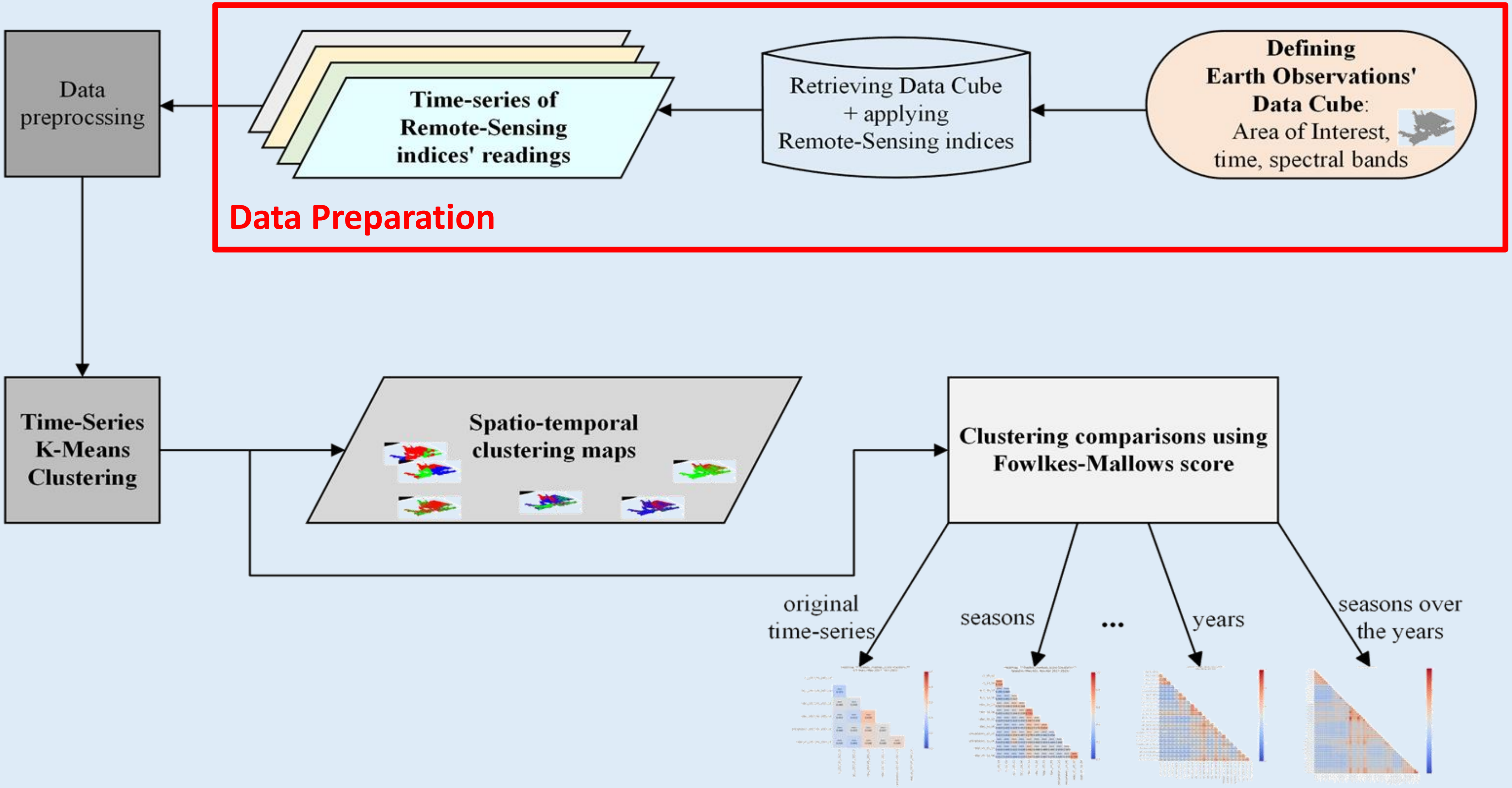
original time-series

seasons

...

years

seasons over the years



Data Preparation

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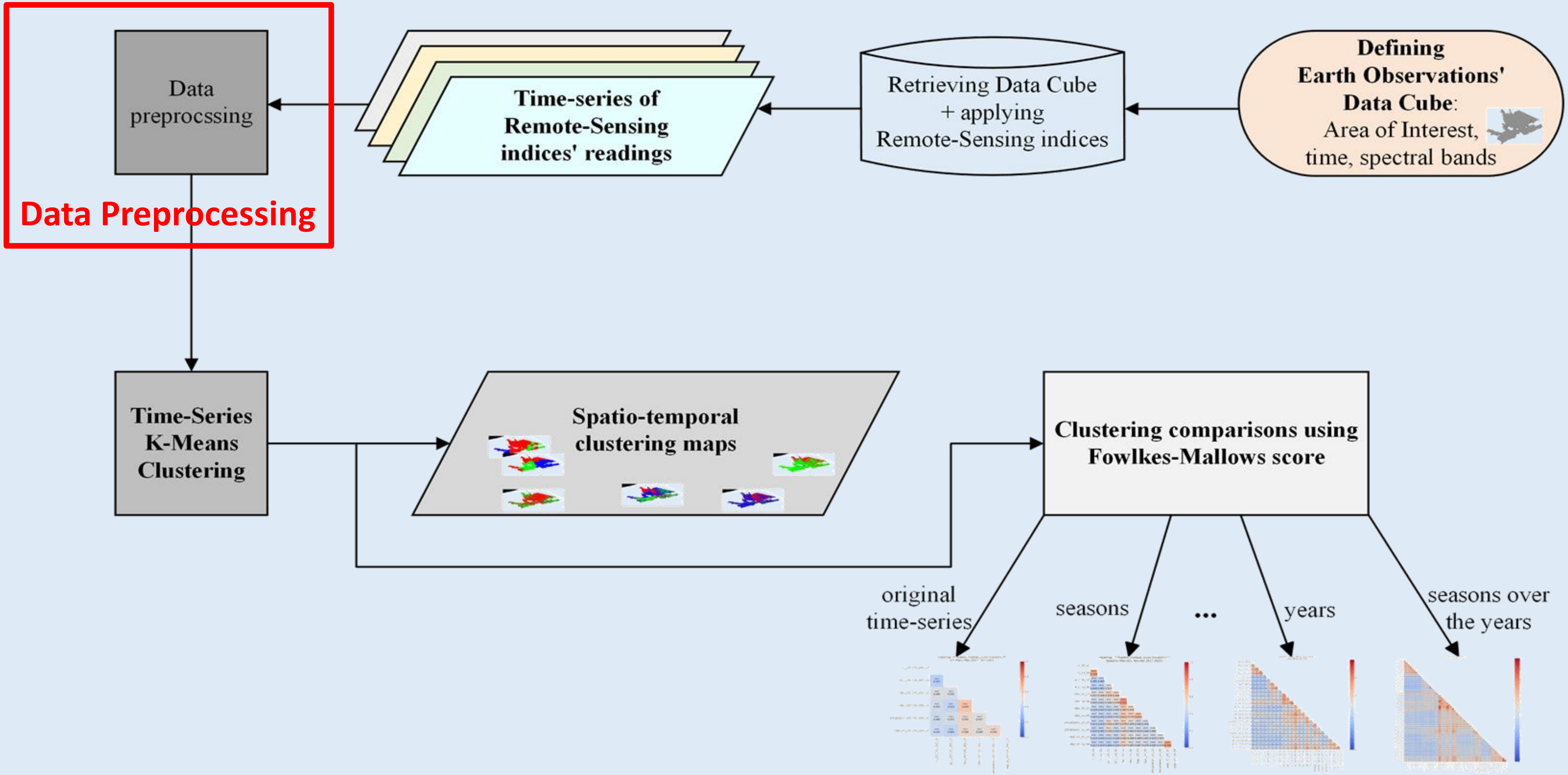

Data preprocssing
Data Preprocessing
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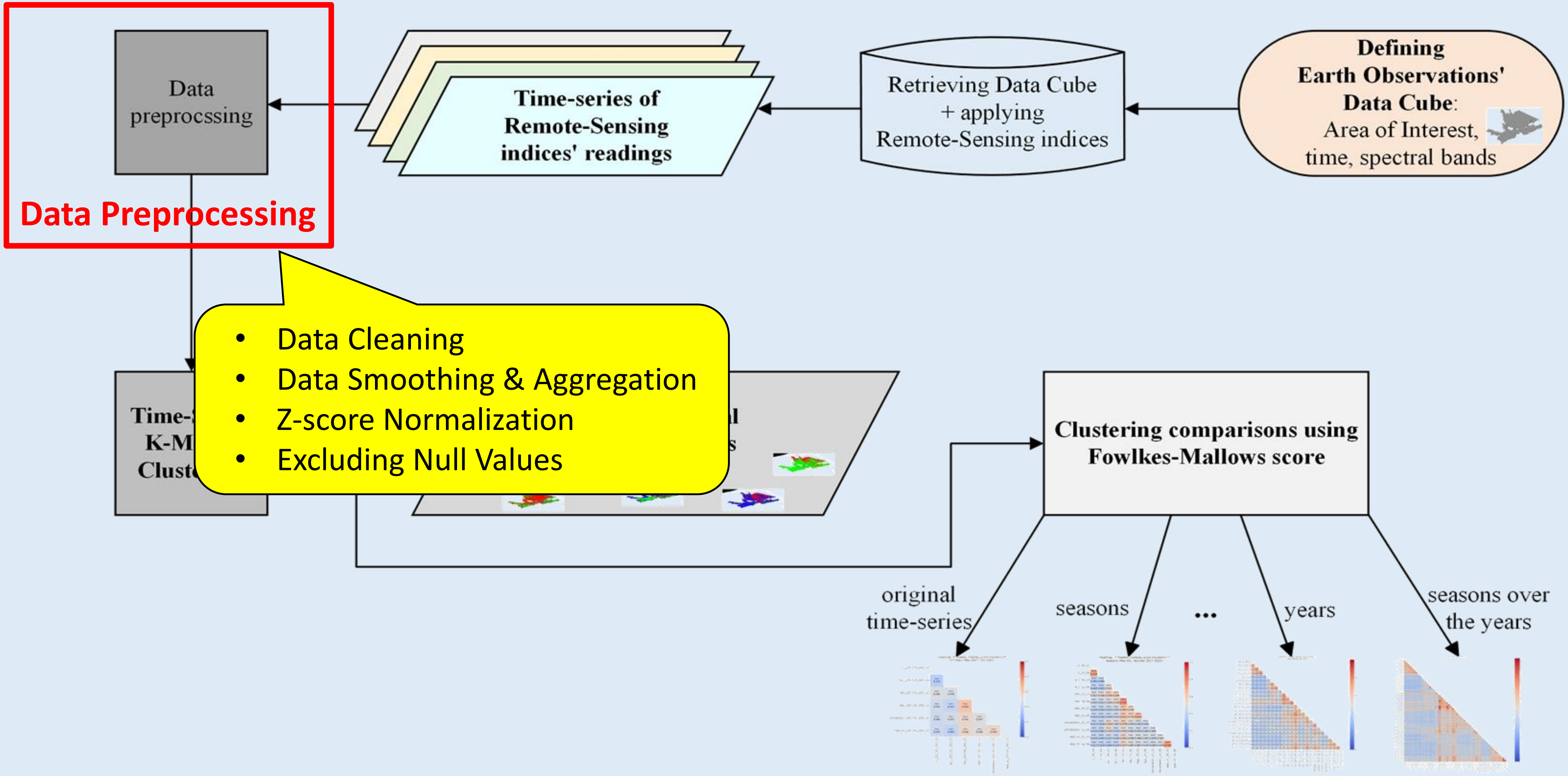
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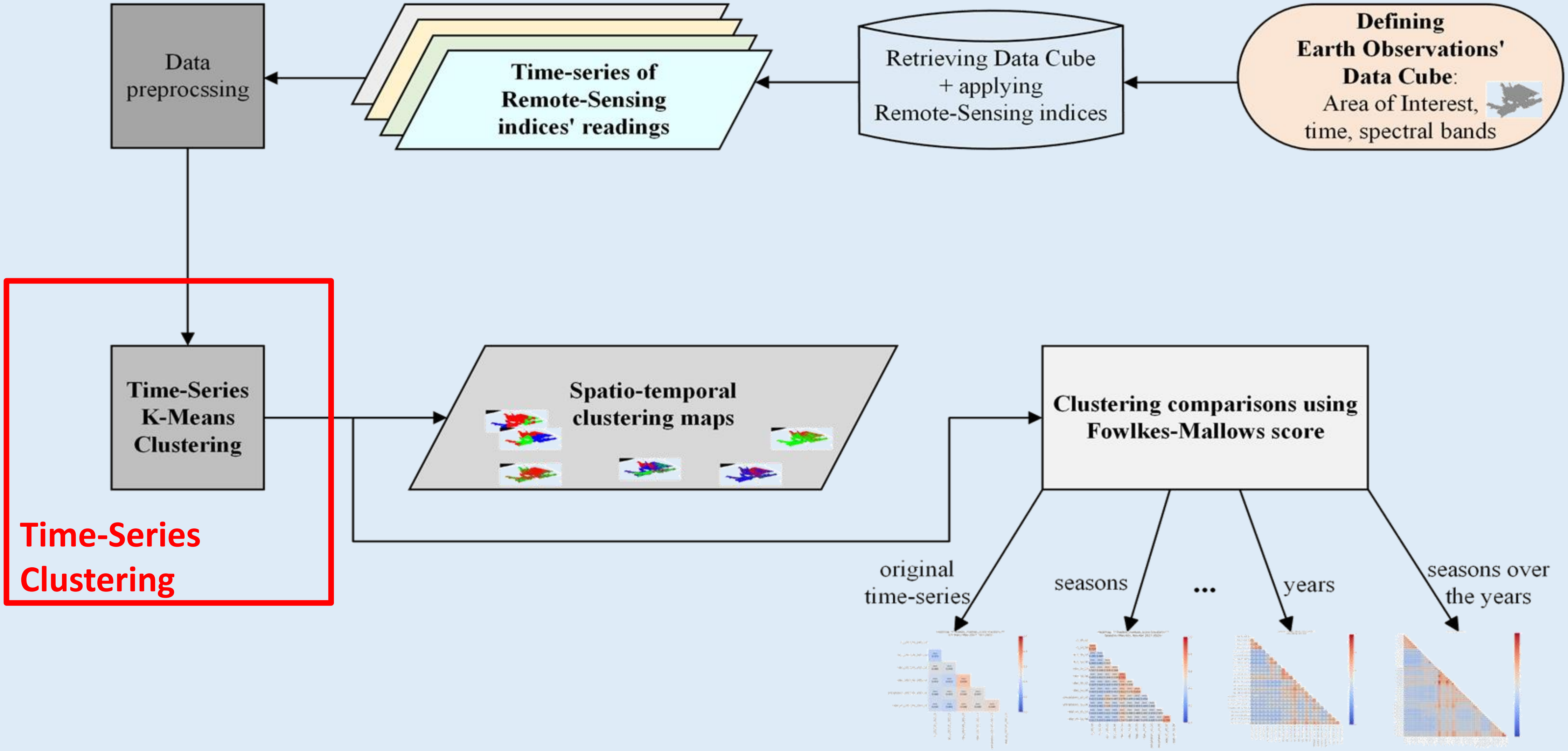
Data Preprocessing

- Data Cleaning
- Data Smoothing & Aggregation
- Z-score Normalization
- Excluding Null Values



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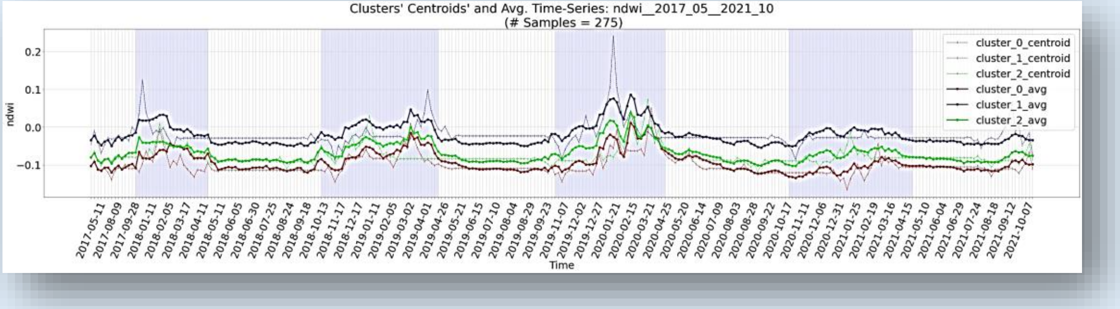
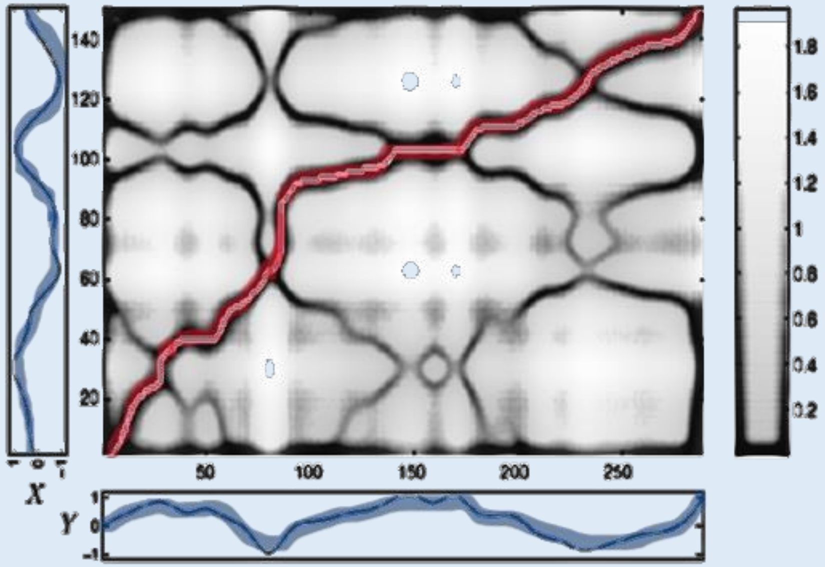
Time-Series Clustering

Time Series Clustering:

- Each RS index original time-series of readings (i.e. during the entire defined time period) is split into the following time **intervals**: seasons (dry/ wet), years (cycles), season each year.
- A **K-Means Clustering** is performed on all n points' time-series, for each time-interval and RS index, using **Dynamic Time Warping (DTW).**



- **Dynamic Time Warping (DTW)**: measuring similarity between two temporal sequences (**X**, **Y**), which may vary in speed and length. A cost/ distance measure is applied on each pair of samples, resulting in a **cost matrix**. The goal is to find an alignment between the sequences having a minimal overall cost ("**warping path**").



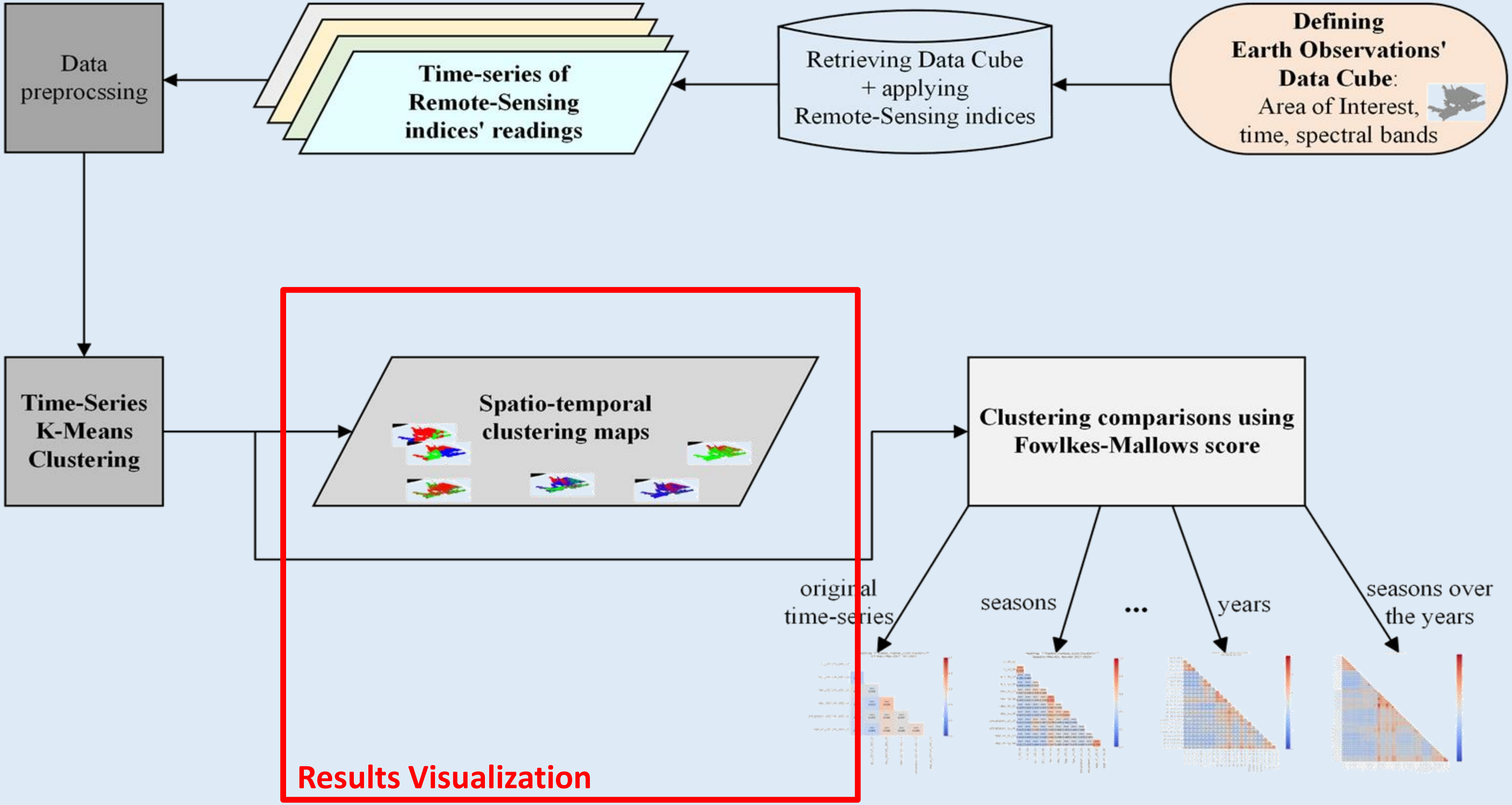
- Here, the similar-shaped time intervals (as determined by the DTW) are grouped into **clusters**. The number of clusters, **K**, is selected beforehand, out of a range of numbers of clusters, if it reached the highest average **Silhouette** score, for all time intervals, of all RS indices.

- **Silhouette Score**: a metric used to evaluate the quality of the clustering configuration. Its value ranges from -1 to 1. ”1” indicates that the clusters are well separated. ”0” means that the clusters are overlapping. ”-1” indicates that the clusters are wrongly assigned.

$$s = \frac{b-a}{\max(a, b)}$$

intra-cluster distance

inter-cluster distance



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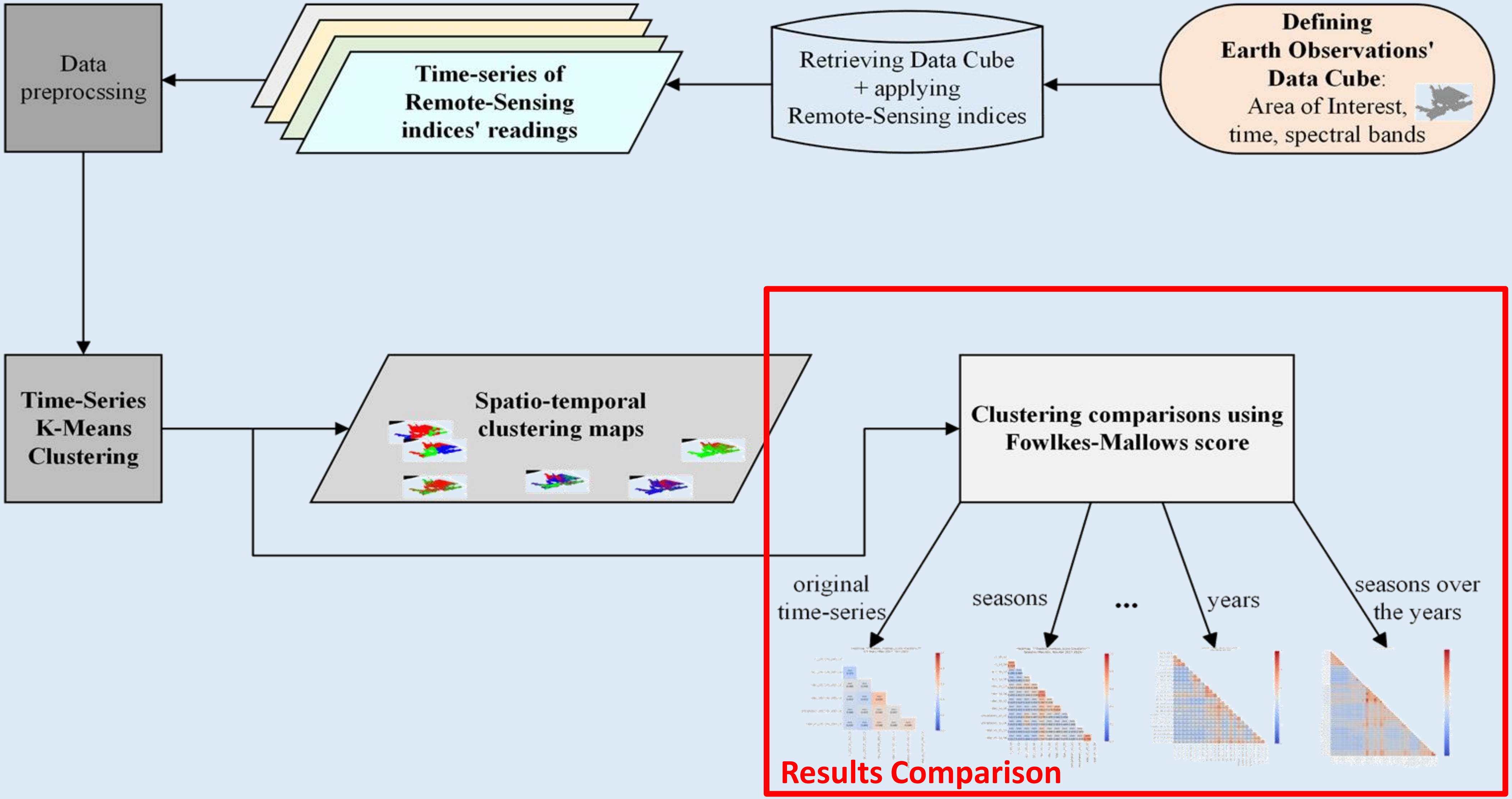
Results Visualization



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Results Comparison

- **Fowlkes-Mallows (FM) Score**: measures similarity between two **clusterings**. The FM can be used to compare either two cluster label sets: S1, S2 (**symmetrical**) or a cluster label set with a true label set. It is defined as the geometric mean between of the precision and recall.

- The score ranges from 0 (totally random) to 1 (identical).

$$\mathrm{FM} = \sqrt{\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}} * \sqrt{\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}}$$

# pairs of points belong to the **same** cluster in both sets

# pairs of points that **don't** belong to S2

# pairs of points that **don't** belong to S1

- **Earth Observations' Data Cube:**
  - **AOI (Area of Interest):** The Israeli-Egyptian Sandfield (n=20,000 points; **uniformly random** within the area).
  - **Time**: May 2017-Oct 2021 (4.5 years).
  - **RS Indices**: CI, LST, NDVI, NDWI, precipitation, RADAR backscatter.
- **Data Retrieval Platform**: GEE (Sentinel 1+2, MODIS, CHIRPS datasets).
- **Data Preprocessing**: filtering high-quality, cloud-free, not null values, MA, aggregation, averaging, normalization.

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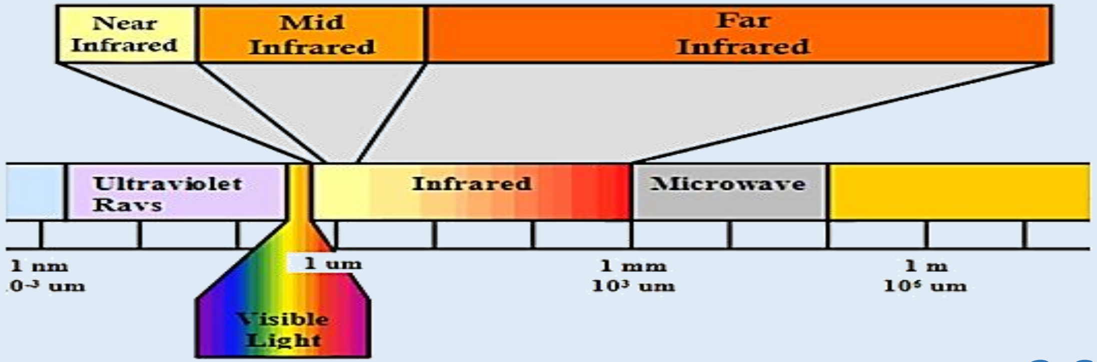
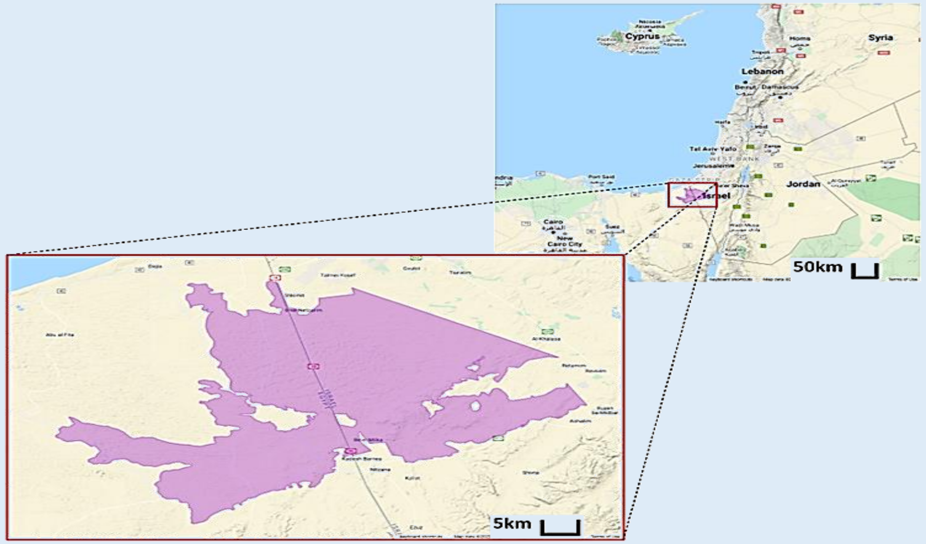
- **Case Study Area:** ***The Israeli-Egyptian Sandfield*** (total area: 1243.86 [km^2], coordinates (center): 31°0'18.9288“N, 34°21'7.6206“E) – is an example of an area which demonstrates particular seasonal optical dynamics in various spectral regions, ranging from **Visible** to **Microwave**, in various **temporal** scales (seasonal, annually, etc.), and the effects of overgazing vs. nature conservation from the two sides of the Israeli-Egyptian border.





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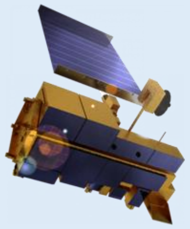
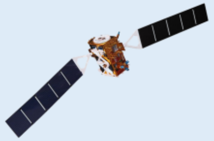
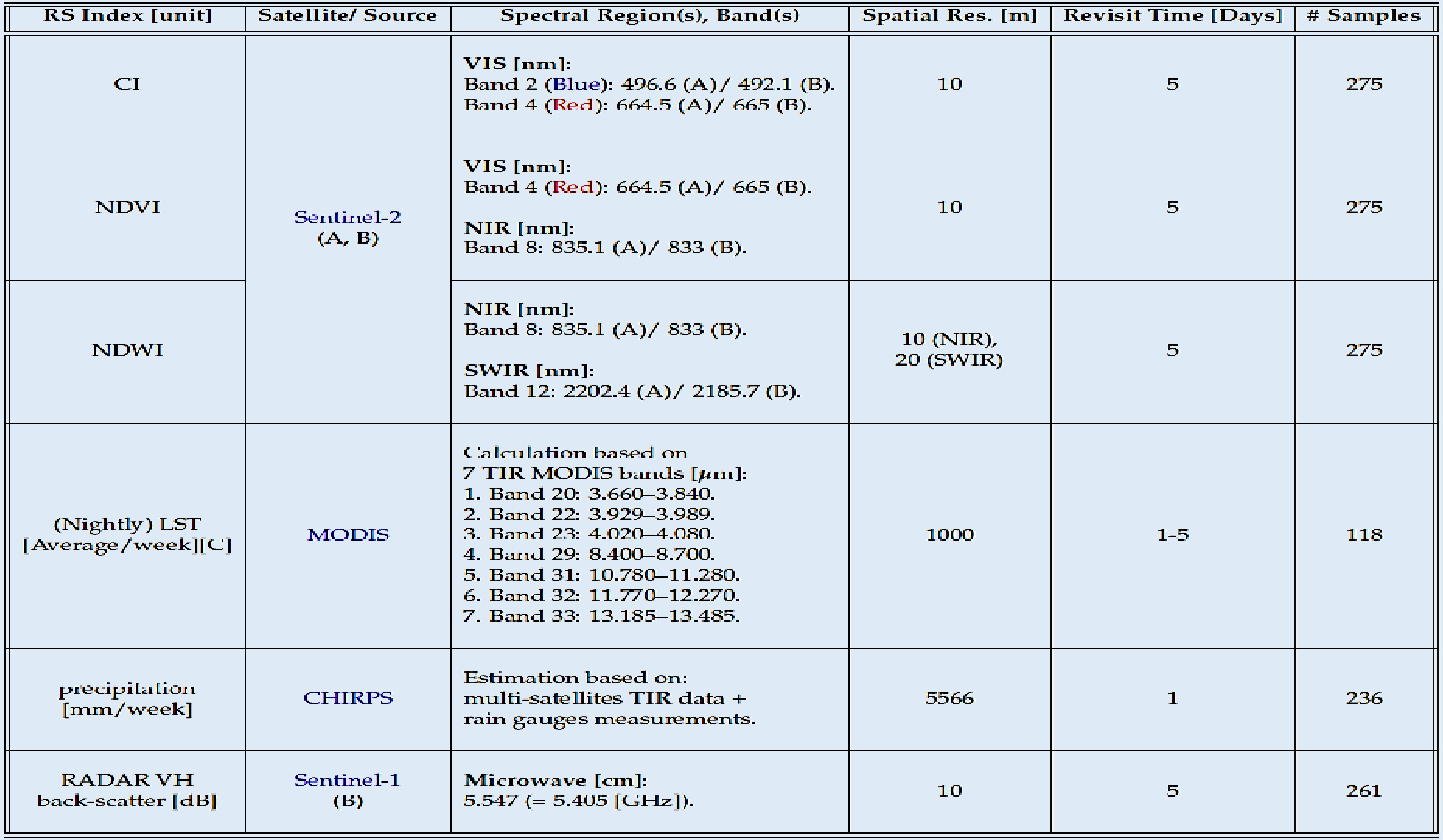
- **Datasets' details:**







RS Index [unit]	Satellite/ Source	Spectral Region(s), Band(s)	Spatial Res. [m]	Revisit Time [Days]	# Samples
CI	Sentinel-2 (A, B)	**VIS [nm]:** Band 2 (Blue): 496.6 (A)/ 492.1 (B). Band 4 (Red): 664.5 (A)/ 665 (B).	10	5	275
NDVI		**VIS [nm]:** Band 4 (Red): 664.5 (A)/ 665 (B). **NIR [nm]:** Band 8: 835.1 (A)/ 833 (B).	10	5	275
NDWI		**NIR [nm]:** Band 8: 835.1 (A)/ 833 (B). **SWIR [nm]:** Band 12: 2202.4 (A)/ 2185.7 (B).	10 (NIR), 20 (SWIR)	5	275
(Nightly) LST [Average/week][C]	MODIS	Calculation based on 7 TIR MODIS bands [μm]: 1. Band 20: 3.660–3.840. 2. Band 22: 3.929–3.989. 3. Band 23: 4.020–4.080. 4. Band 29: 8.400–8.700. 5. Band 31: 10.780–11.280. 6. Band 32: 11.770–12.270. 7. Band 33: 13.185–13.485.	1000	1-5	118
precipitation [mm/week]	CHIRPS	Estimation based on: multi-satellites TIR data + rain gauges measurements.	5566	1	236
RADAR VH back-scatter [dB]	Sentinel-1 (B)	**Microwave [cm]:** 5.547 (= 5.405 [GHz]).	10	5	261

Climate Hazards Center UC SANTA BARBARA · USAID FROM THE AMERICAN PEOPLE · UC SANTA BARBARA Geography

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- **Data Preprocessing**: filtering high-quality, cloud-free, not null values, MA, aggregation, averaging, normalization.

Data preprocessing steps:

1. **Filtering only high-quality readings**: relevant to: **LST** (using MODIS' quality band: “QC_Night”; 954 samples out of 975; 97.846%; before weekly aggregation) and **RADAR** (268 samples).
2. **Filtering only cloud-free readings**: relevant to: **CI**, **NDVI**, **NDWI**. Information provided by the ”QA60” cloud mask band of Sentinel-2 sensor. There were 244.342 cloud-free samples in average out of 301 (81.177%).
3. **Excluding null values**: in all datasets.

Data preprocessing steps (cont.):

4. **Synchronization of dates**: in all RS indices, for all 20,000 time-series.
5. **Applying Moving Average (MA) to remove noise**: e.g. of two-weeks time in **CI**, **NDVI** and **NDWI**, to overcome missing data due to cloudness, and null values.
6. **Weekly aggregation**: relevant to **precipitation** dataset (1645 → 236 samples).
7. **Weekly averaging**: relevant to **LST** dataset (954 → 232 samples).
8. **Z-score normalization**: of all datasets.

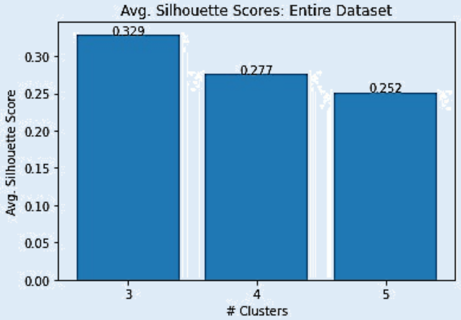
Time Intervals (#):

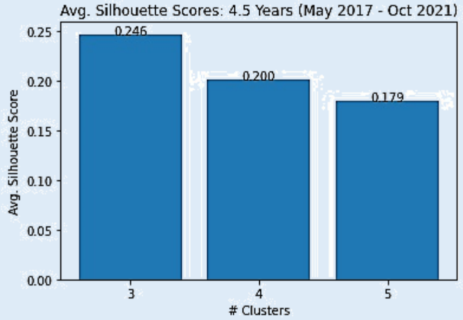
- **Original time-series**: 4.5 years – May 2017-Oct 2021 (1).
- **Seasons**: dry (May-Oct) and wet (Nov-Apr) seasons (2).
- **Years** (Cycles): May-Apr (4).
- **Season each year**: dry/ wet season of each year cycle (9).

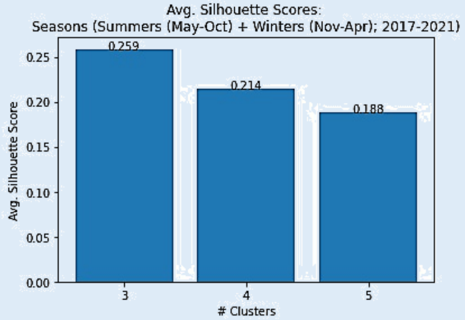
→ Total # of time intervals for each RS index = **16** (=1+2+4+9).

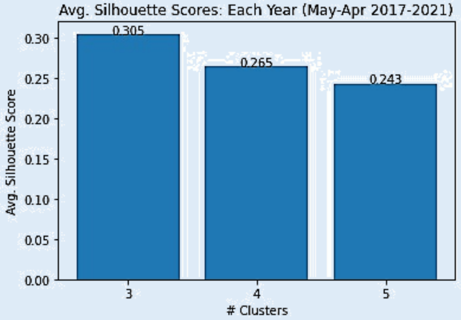
Time Series Clustering:

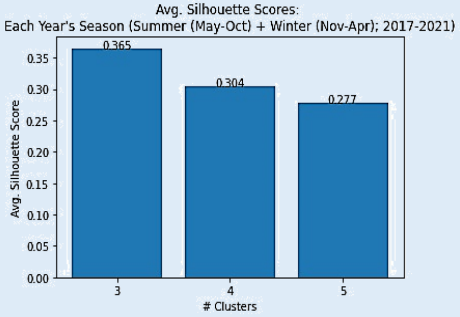
- **K**-Means Clustering of each interval, for all 20,000 points in AOI, using **DTW**.
- **K=3** (=highest average Silhouette Score out of a range of **3-5** clusters):





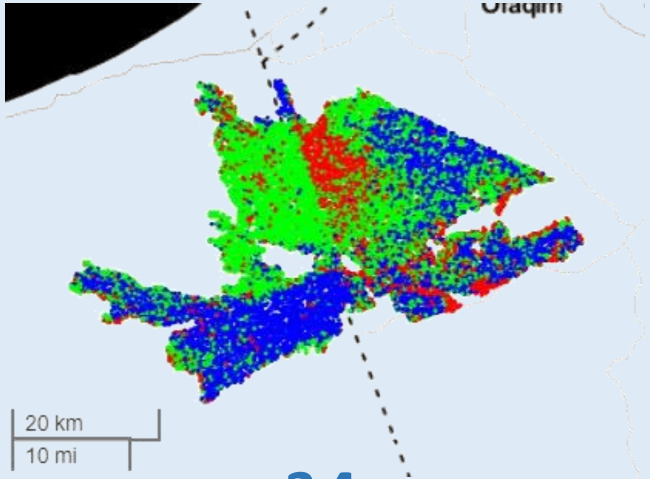






Results Visualization – Spatio-Temporal Clustering Maps:

- **96** clustering maps were generated out of all clustering results of the 20,000 points (= **6** RS indices * **16** time intervals).
- **Example**: clustering map of CI during 2017’s dry season (May-Oct):



Results Comparison using Fowlkes-Mallows (FM) Score between:

- ***Different*** time intervals’ **clusterings**, of the ***same*** RS index.
- ***Same*** time intervals’ **clusterings**, of ***different*** RS indices.
- ***Different*** time intervals’ **clusterings**, of ***different*** RS indices.

➔ FM heat-maps.

Software and hardware information:

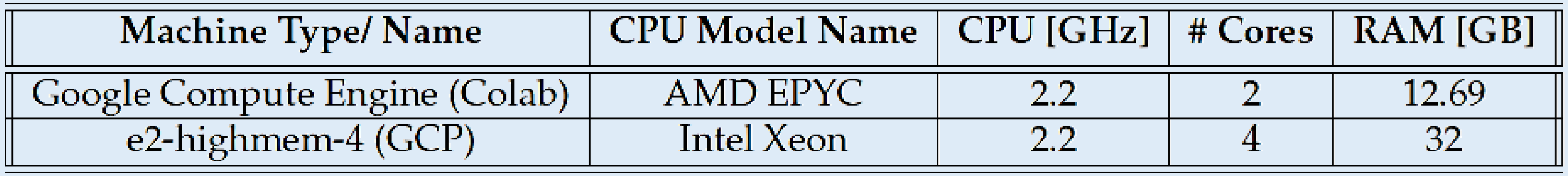
- **Javascript** (datasets generation), **Python** (clustering: *tslearn*,

  analysis + maps: *sklearn, seaborn, folium*).

- **Total datasets size** (tabular; after preprocessing): ~600 [MB].

- Total time-series clustering **running time** (of all 96 intervals): ~6-7 [days].

- **Hardware specifications**:

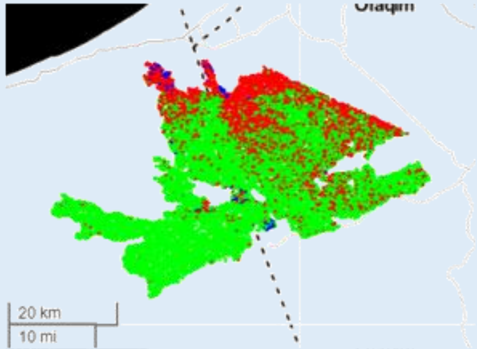


Machine Type/ Name	CPU Model Name	CPU [GHz]	# Cores	RAM [GB]
Google Compute Engine (Colab)	AMD EPYC	2.2	2	12.69
e2-highmem-4 (GCP)	Intel Xeon	2.2	4	32

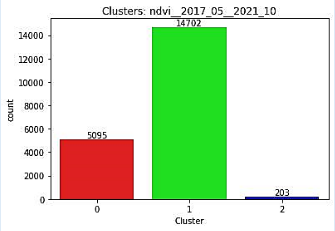
- **Evaluation**: The were no ground-truth labelling. The whole clustering process was **unsupervised**. The estimation of the reliability of the results was done by Prof. Karnieli & Dr. Micha Silver.
- **Statistical Significance**: of each FM result was calculated using ”**Bootstrapping**” procedure with 1000 permutations of each clustering result.

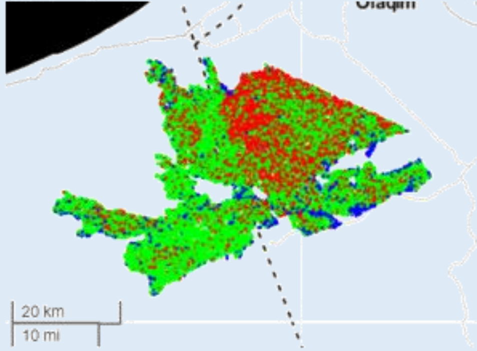
Examples:

- 4.5 years (May 2017-Oct 2021):

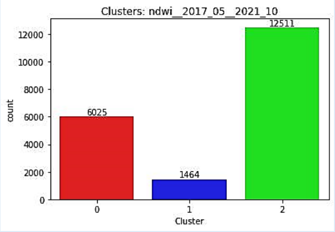


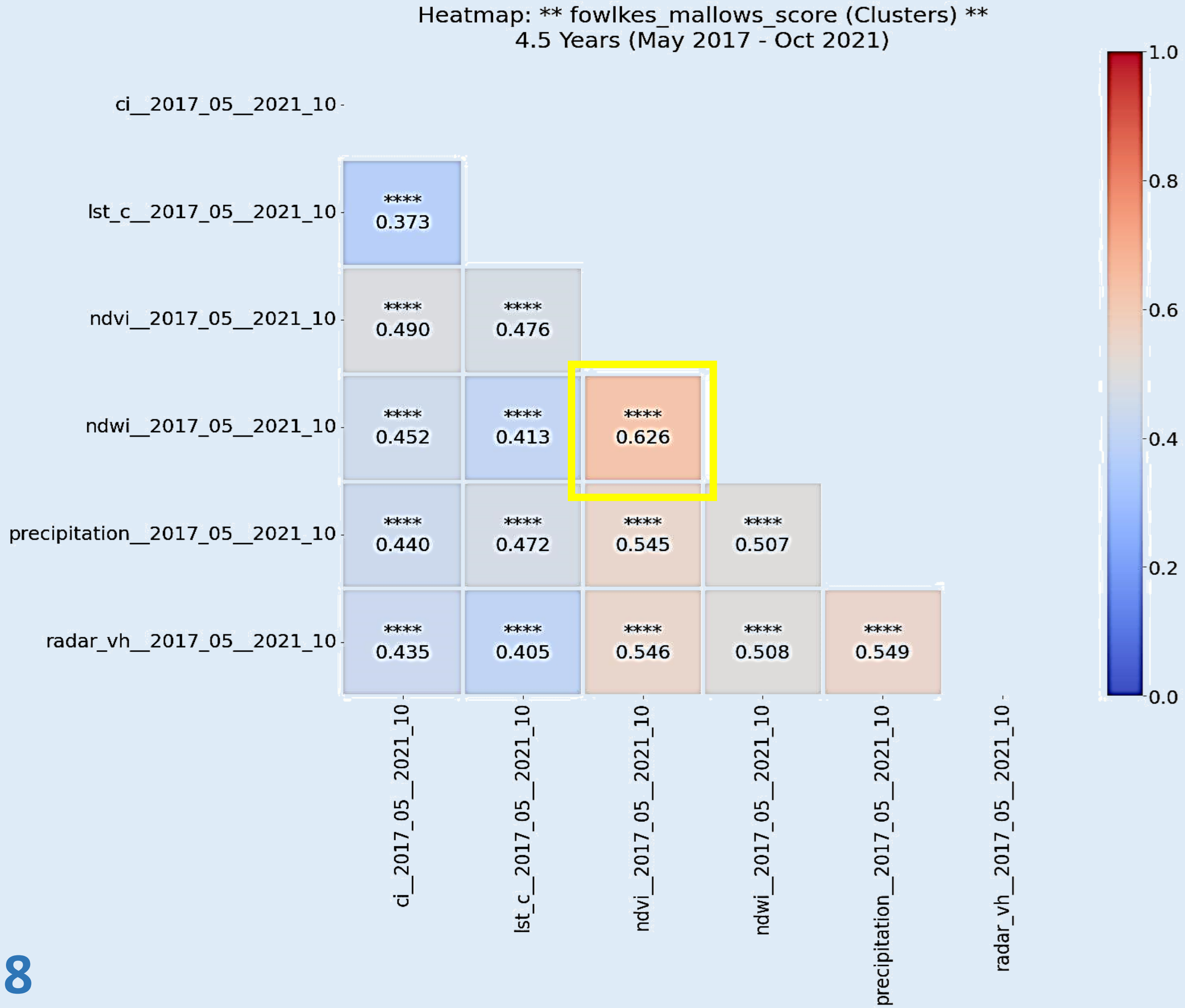
NDVI





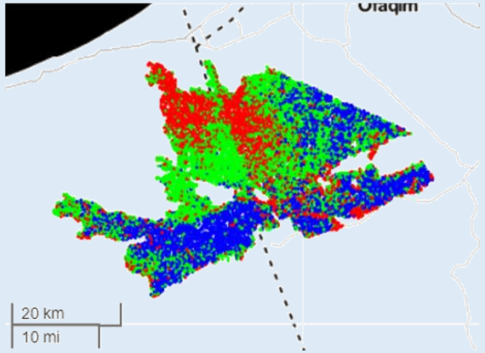
NDWI



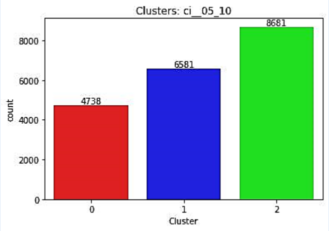


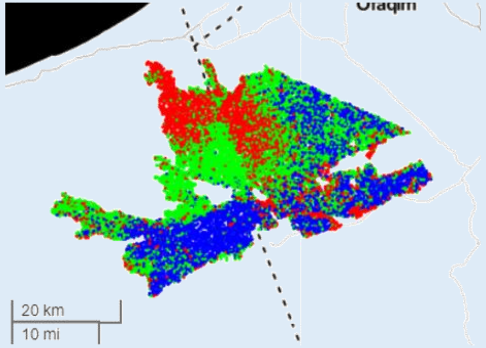
- Seasons: May-Oct vs. Nov-Apr

  (dry vs. wet seasons):

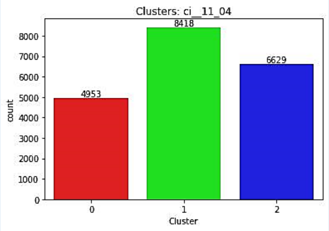


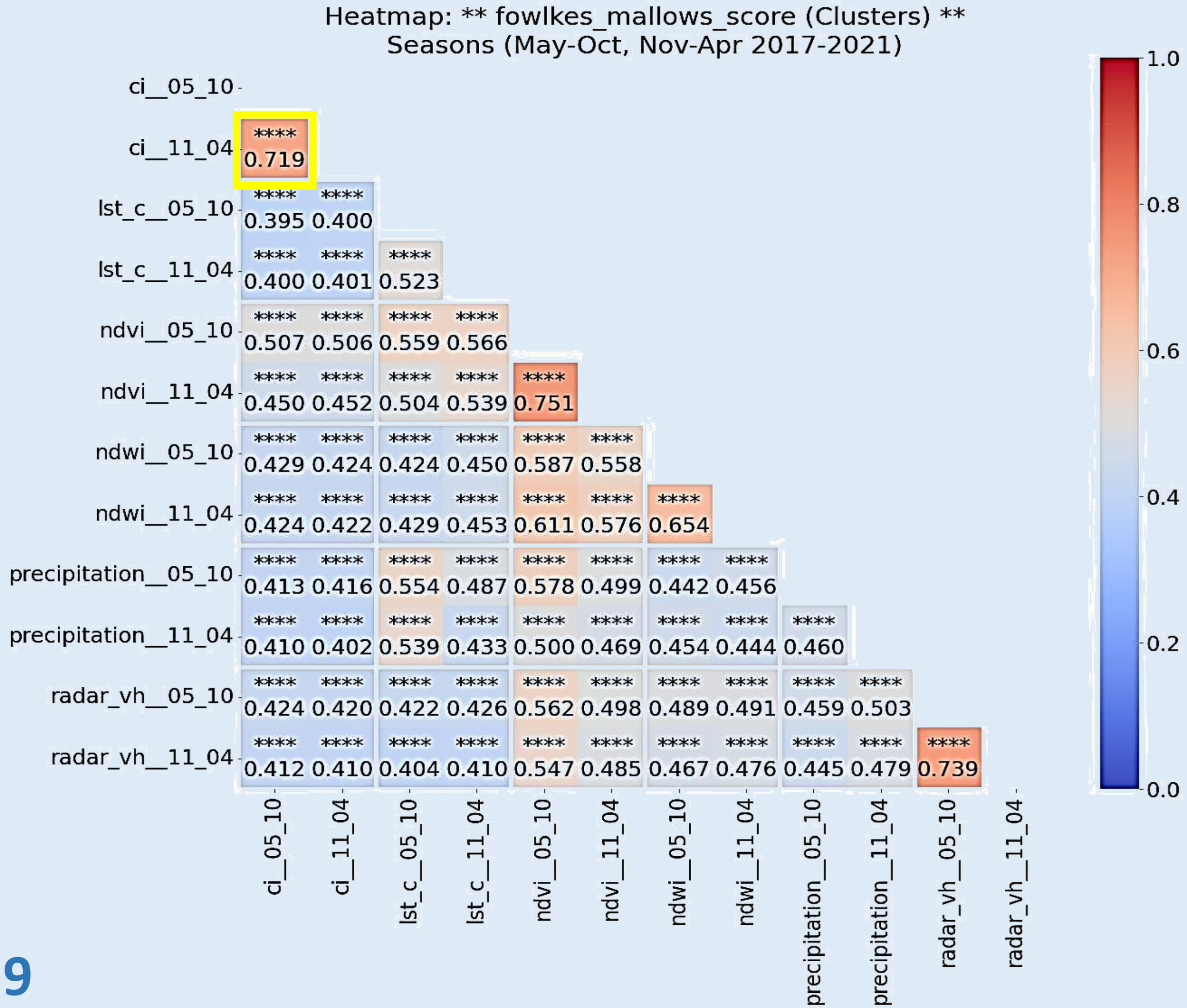
CI (dry)





CI (wet)



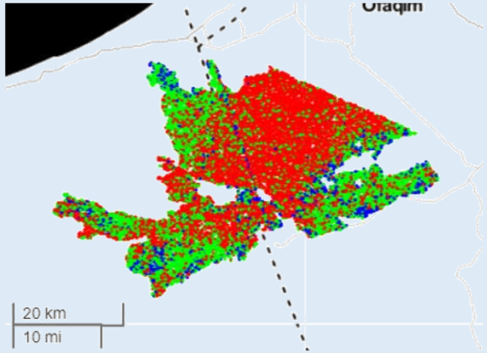


Heatmap: ** fowlkes_mallows_score (Clusters) **
Seasons (May-Oct, Nov-Apr 2017-2021)

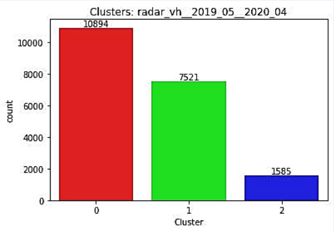
	ci__05_10	ci__11_04	lst_c__05_10	lst_c__11_04	ndvi__05_10	ndvi__11_04	ndwi__05_10	ndwi__11_04	precipitation__05_10	precipitation__11_04	radar_vh__05_10	radar_vh__11_04
ci__05_10												
ci__11_04	**** 0.719											
lst_c__05_10	**** 0.395	**** 0.400										
lst_c__11_04	**** 0.400	**** 0.401	**** 0.523									
ndvi__05_10	**** 0.507	**** 0.506	**** 0.559	**** 0.566								
ndvi__11_04	**** 0.450	**** 0.452	**** 0.504	**** 0.539	**** 0.751							
ndwi__05_10	**** 0.429	**** 0.424	**** 0.424	**** 0.450	**** 0.587	**** 0.558						
ndwi__11_04	**** 0.424	**** 0.422	**** 0.429	**** 0.453	**** 0.611	**** 0.576	**** 0.654					
precipitation__05_10	**** 0.413	**** 0.416	**** 0.554	**** 0.487	**** 0.578	**** 0.499	**** 0.442	**** 0.456				
precipitation__11_04	**** 0.410	**** 0.402	**** 0.539	**** 0.433	**** 0.500	**** 0.469	**** 0.454	**** 0.444	**** 0.460			
radar_vh__05_10	**** 0.424	**** 0.420	**** 0.422	**** 0.426	**** 0.562	**** 0.498	**** 0.489	**** 0.491	**** 0.459	**** 0.503		
radar_vh__11_04	**** 0.412	**** 0.410	**** 0.404	**** 0.410	**** 0.547	**** 0.485	**** 0.467	**** 0.476	**** 0.445	**** 0.479	**** 0.739	

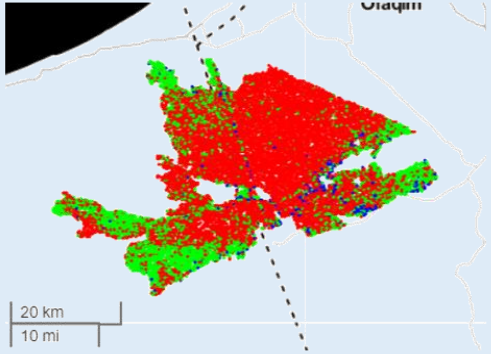
- Year cycles (May-Apr)

  during May 2017-Apr 2021:

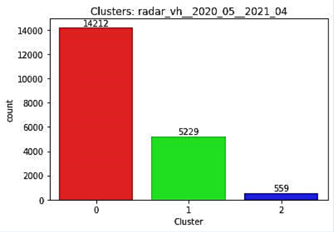


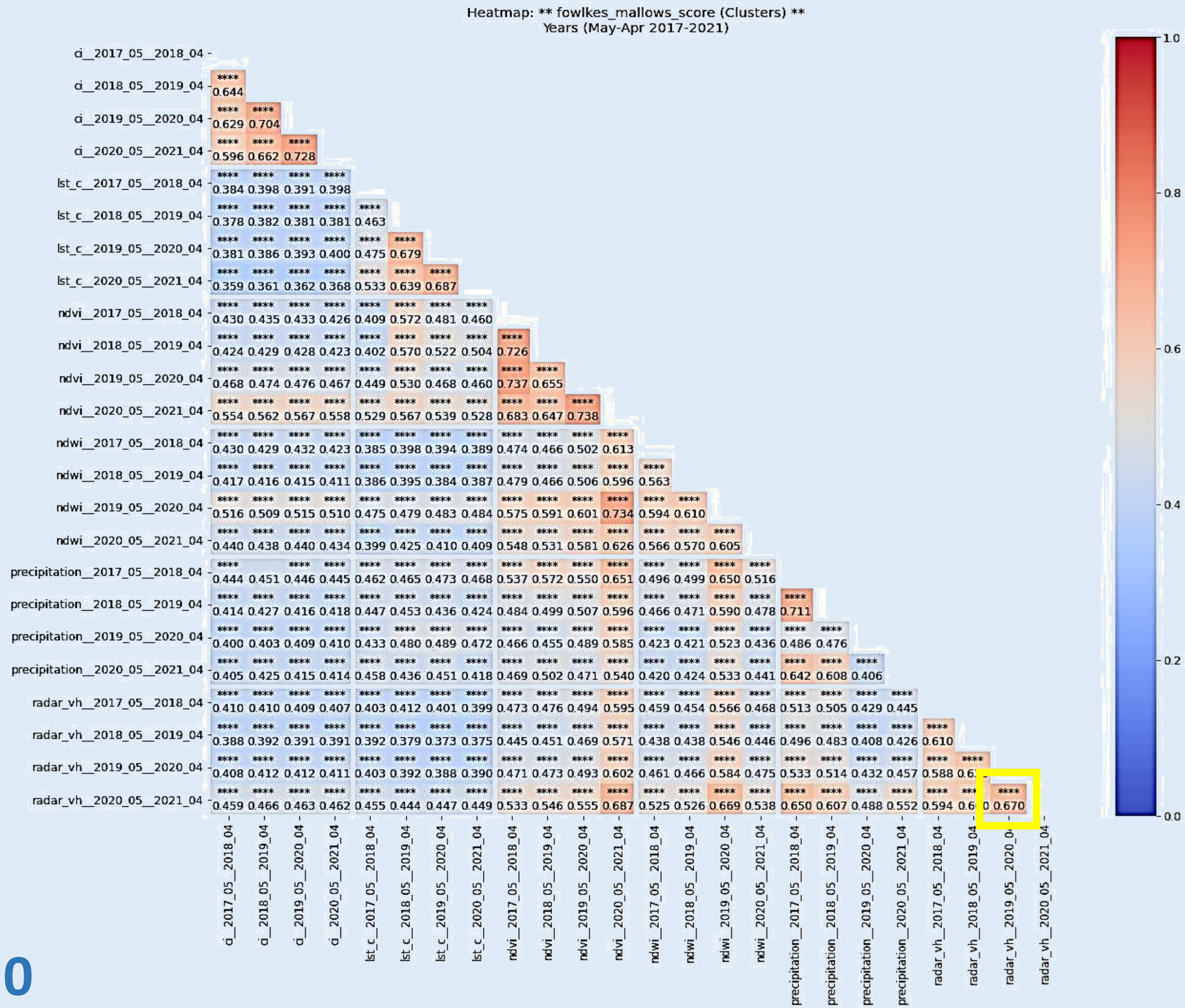
RADAR (May `19-Apr `20)





RADAR (May `20-Apr `21)




Heatmap: ** fowlkes_mallows_score (Clusters) **
Years (May-Apr 2017-2021)

	ci__2017_05__2018_04	ci__2018_05__2019_04	ci__2019_05__2020_04	ci__2020_05__2021_04	lst_c__2017_05__2018_04	lst_c__2018_05__2019_04	lst_c__2019_05__2020_04	lst_c__2020_05__2021_04	ndvi__2017_05__2018_04	ndvi__2018_05__2019_04	ndvi__2019_05__2020_04	ndvi__2020_05__2021_04	ndwi__2017_05__2018_04	ndwi__2018_05__2019_04	ndwi__2019_05__2020_04	ndwi__2020_05__2021_04	precipitation__2017_05__2018_04	precipitation__2018_05__2019_04	precipitation__2019_05__2020_04	precipitation__2020_05__2021_04	radar_vh__2017_05__2018_04	radar_vh__2018_05__2019_04	radar_vh__2019_05__2020_04	radar_vh__2020_05__2021_04
ci__2017_05__2018_04																								
ci__2018_05__2019_04	**** 0.644																							
ci__2019_05__2020_04	**** 0.629	**** 0.704																						
ci__2020_05__2021_04	**** 0.596	**** 0.662	**** 0.728																					
lst_c__2017_05__2018_04	**** 0.384	**** 0.398	**** 0.391	**** 0.398																				
lst_c__2018_05__2019_04	**** 0.378	**** 0.382	**** 0.381	**** 0.381	**** 0.463																			
lst_c__2019_05__2020_04	**** 0.381	**** 0.386	**** 0.393	**** 0.400	**** 0.475	**** 0.679																		
lst_c__2020_05__2021_04	**** 0.359	**** 0.361	**** 0.362	**** 0.368	**** 0.533	**** 0.639	**** 0.687																	
ndvi__2017_05__2018_04	**** 0.430	**** 0.435	**** 0.433	**** 0.426	**** 0.409	**** 0.572	**** 0.481	**** 0.460																
ndvi__2018_05__2019_04	**** 0.424	**** 0.429	**** 0.428	**** 0.423	**** 0.402	**** 0.570	**** 0.522	**** 0.504	**** 0.726															
ndvi__2019_05__2020_04	**** 0.468	**** 0.474	**** 0.476	**** 0.467	**** 0.449	**** 0.530	**** 0.468	**** 0.460	**** 0.737	**** 0.655														
ndvi__2020_05__2021_04	**** 0.554	**** 0.562	**** 0.567	**** 0.558	**** 0.529	**** 0.567	**** 0.539	**** 0.528	**** 0.683	**** 0.647	**** 0.738													
ndwi__2017_05__2018_04	**** 0.430	**** 0.429	**** 0.432	**** 0.423	**** 0.385	**** 0.398	**** 0.394	**** 0.389	**** 0.474	**** 0.466	**** 0.502	**** 0.613												
ndwi__2018_05__2019_04	**** 0.417	**** 0.416	**** 0.415	**** 0.411	**** 0.386	**** 0.395	**** 0.384	**** 0.387	**** 0.479	**** 0.466	**** 0.506	**** 0.596	**** 0.563											
ndwi__2019_05__2020_04	**** 0.516	**** 0.509	**** 0.515	**** 0.510	**** 0.475	**** 0.479	**** 0.483	**** 0.484	**** 0.575	**** 0.591	**** 0.601	**** 0.734	**** 0.594	**** 0.610										
ndwi__2020_05__2021_04	**** 0.440	**** 0.438	**** 0.440	**** 0.434	**** 0.399	**** 0.425	**** 0.410	**** 0.409	**** 0.548	**** 0.531	**** 0.581	**** 0.626	**** 0.566	**** 0.570	**** 0.605									
precipitation__2017_05__2018_04	**** 0.444	0.451	**** 0.446	**** 0.445	**** 0.462	**** 0.465	**** 0.473	**** 0.468	**** 0.537	**** 0.572	**** 0.550	**** 0.651	**** 0.496	**** 0.499	**** 0.650	**** 0.516								
precipitation__2018_05__2019_04	**** 0.414	**** 0.427	**** 0.416	**** 0.418	**** 0.447	**** 0.453	**** 0.436	**** 0.424	**** 0.484	**** 0.499	**** 0.507	**** 0.596	**** 0.466	**** 0.471	**** 0.590	**** 0.478	**** 0.711							
precipitation__2019_05__2020_04	**** 0.400	**** 0.403	**** 0.409	**** 0.410	**** 0.433	**** 0.480	**** 0.489	**** 0.472	**** 0.466	**** 0.455	**** 0.489	**** 0.585	**** 0.423	**** 0.421	**** 0.523	**** 0.436	**** 0.486	**** 0.476						
precipitation__2020_05__2021_04	**** 0.405	**** 0.425	**** 0.415	**** 0.414	**** 0.458	**** 0.436	**** 0.451	**** 0.418	**** 0.469	**** 0.502	**** 0.471	**** 0.540	**** 0.420	**** 0.424	**** 0.533	**** 0.441	**** 0.642	**** 0.608	**** 0.406					
radar_vh__2017_05__2018_04	**** 0.410	**** 0.410	**** 0.409	**** 0.407	**** 0.403	**** 0.412	**** 0.401	**** 0.399	**** 0.473	**** 0.476	**** 0.494	**** 0.595	**** 0.459	**** 0.454	**** 0.566	**** 0.468	**** 0.513	**** 0.505	**** 0.429	**** 0.445				
radar_vh__2018_05__2019_04	**** 0.388	**** 0.392	**** 0.391	**** 0.391	**** 0.392	**** 0.379	**** 0.373	**** 0.375	**** 0.445	**** 0.451	**** 0.469	**** 0.571	**** 0.438	**** 0.438	**** 0.546	**** 0.446	**** 0.496	**** 0.483	**** 0.408	**** 0.426	**** 0.610			
radar_vh__2019_05__2020_04	**** 0.408	**** 0.412	**** 0.412	**** 0.411	**** 0.403	**** 0.392	**** 0.388	**** 0.390	**** 0.471	**** 0.473	**** 0.493	**** 0.602	**** 0.461	**** 0.466	**** 0.584	**** 0.475	**** 0.533	**** 0.514	**** 0.432	**** 0.457	**** 0.588	**** 0.6[illegible]		
radar_vh__2020_05__2021_04	**** 0.459	**** 0.466	**** 0.463	**** 0.462	**** 0.455	**** 0.444	**** 0.447	**** 0.449	**** 0.533	**** 0.546	**** 0.555	**** 0.687	**** 0.525	**** 0.526	**** 0.669	**** 0.538	**** 0.650	**** 0.607	**** 0.488	**** 0.552	**** 0.594	**** 0.6[illegible]0	**** 0.670	

- The highest similarity was between the **NDVI** and **NDWI** clusterings (together they reached the highest average FM scores). It fits the assumption that both clusterings will be similar as they reflect **vegetation health**.
- In terms of a single RS index, the: **RADAR**, **CI**, and **NDVI**’s clustering behaviors maintained high level of similarity between the dry and the wet seasons (FM ≥ 0.719). This indicates that the surface topography, biocrust, and vegetation cover remained stable regardless the season.

Future work:

- Writing a paper (Remote Sensing).
- **Implementation**: apply the model on other AOIs; more/ other RS indices; longer period of data (= detect long-term patterns/ changes).
- **Methodology**: using/ comparing with other clustering algorithms (e.g. Hierarchical, deep learning); different approach – spatial clustering (e.g. DBSCAN); ensemble of different clustering algorithms/ results.

Thank you!