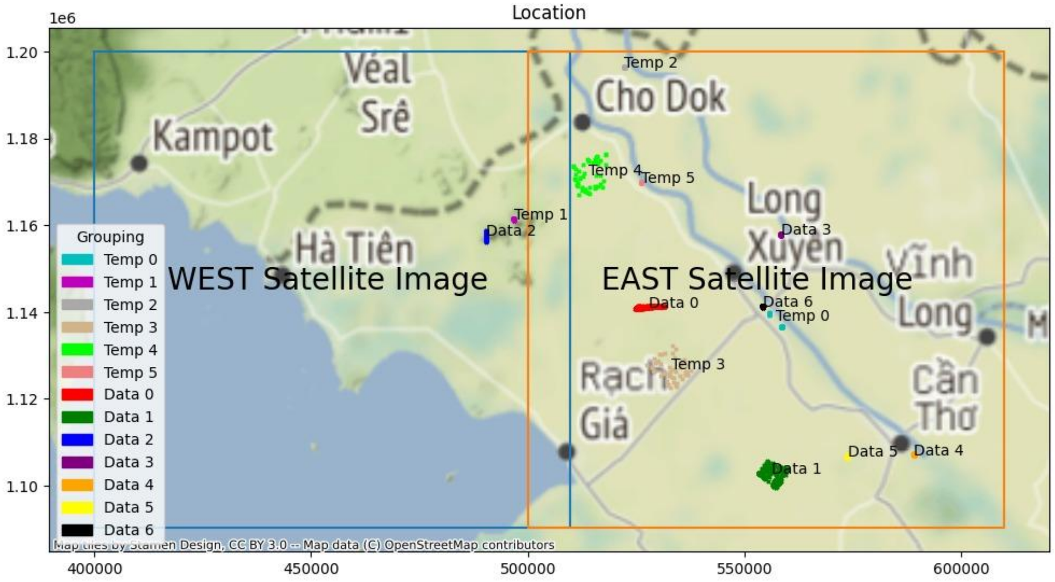
2023 EY Open Science Data Challenge - Level 1

To develop a predictive model that can detect the presence, or non-presence of rice field at a given location based on satellite data. (Binary classification)

Dataset

Latitude and Longitude	Class of Land
(9.98941462845174, 105.4991893167462)	Rice
(9.97351661941364, 105.53643608077667)	Rice
(9.97533353473228, 105.52144652939856)	Rice
(9.9671574157984, 105.49373857079053)	Rice
(9.967611644628061, 105.50827389333898)	Rice
(9.982601196006842, 105.51690424110214)	Rice
(9.9830554248365, 105.53825299609522)	Rice
(9.968520102287382, 105.4946470284498)	Rice
(9.974425077072961, 105.50645697802042)	Rice
(9.96397781399078, 105.52371767354674)	Rice
(9.991685772600041, 105.51645001227251)	Rice
(9.985780797814462, 105.50872812216863)	Rice
(9.981238509517862, 105.50373160504259)	Rice
(9.971699704095002, 105.4923758843016)	Rice
(9.95307632207894, 105.51599578344286)	Rice
(9.97987582302888, 105.51554155461324)	Rice
(10.481616988271316, 104.91150805695796)	Non Rice
(10.481162759441657, 104.91150805695796)	Non Rice
(10.480708530611997, 104.91150805695796)	Non Rice
(10.480254301782336, 104.91150805695796)	Non Rice
(10.479800072952678, 104.91150805695796)	Non Rice
(10.479345844123017, 104.91150805695796)	Non Rice
(10.478891615293357, 104.91150805695796)	Non Rice



Satellite data for the 600 data points spanning across Jan 2021 to Dec 2021 are sampled based on various conditions to provide comprehensive information for the model to classify the rice fields.

Satellite Data Collection

The satellite data of various wavelength bands and dates is accessed through Microsoft Planetary Computer Hub with Python API.

<u>Data Sources</u>

Sentinel-1 (radar data): VH, VV (can penetrate cloud (useful for target site which has high moisture and is often cloudy))

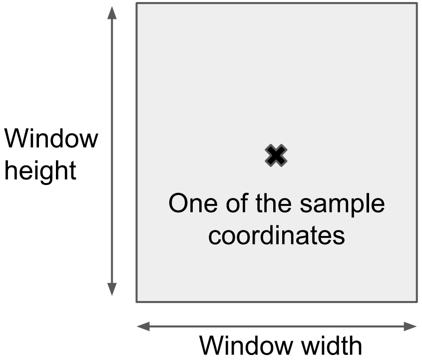
Sentinel-2 (optical data) data: B01, B02, B03, B04, B05, B06, B07, B08, B8A, B09, B11, B12, SCL, WVP, visual. (more informative but unable to penetrate cloud)

Collected Data

Satellite data collected is saved in multiple files with each of them containing satellite data of a particular source (s1 or s2) and date. e.g. LEVEL1_SENTINEL-2-L2A_2021-02-09 with satellite data collected from Sentinel 2 for 2021-02-09 along with their corresponding coordinates.is shown below.

Latitude and Longitude	lass of Lan	AOT	B02	B03	B04	B08	WVP	visual	AOT_w5	B02_w5	B03_w5	B04_w5	B08_w5	WVP_w5	visual_w5
(10.323727047081501, 105.2516346045924)	Rice	204	437	550	343	4212	4246	35	[[204. 204	[[452. 428	[[668. 639	[[385. 378	[[5128. 46	[[4560. 42	[[40. 39. 4
(10.322364360592521, 105.27843410554115)	Rice	204	1440	1544	1238	3450	4377	126	[[204. 204	[[693. 87	[[780. 94	[[617. 81	[[2426. 26	[[4121. 41	[[63. 83.
(10.321455902933202, 105.25254306225168)	Rice	204	431	594	326	4380	4750	34	[[204. 204	[[428. 433	[[511. 508	[[314. 301	[[3294. 32	[[4631. 46	[[32. 31. 3
(10.324181275911162, 105.25118037576274)	Rice	204	513	735	427	5756	4311	44	[[204. 204	[[492. 519	[[648. 658	[[381. 394	[[5424. 54	[[4275. 42	[[39. 41. 5
(10.324635504740822, 105.27389181724476)	Rice	204	3046	3276	3244	6496	4377	255	[[204. 204	[[2264. 30	[[2410. 32	[[2320. 28	[[5868. 62	[[4377. 43	[[236. 255
(10.323727047081501, 105.28070524968936)	Rice	204	385	467	326	2234	4093	34	[[204. 204	[[388. 386	[[463. 445	[[310. 292	[[2150. 20	[[4038. 40	[[32. 30. 3
(10.325089733570481, 105.23937042619212)	Rice	204	4796	4608	4078	7328	4377	255	[[204. 204	[[3554. 36	[[3200. 31	[[2546. 24	[[6480. 65	[[4377. 43	[[255. 246

Satellite data

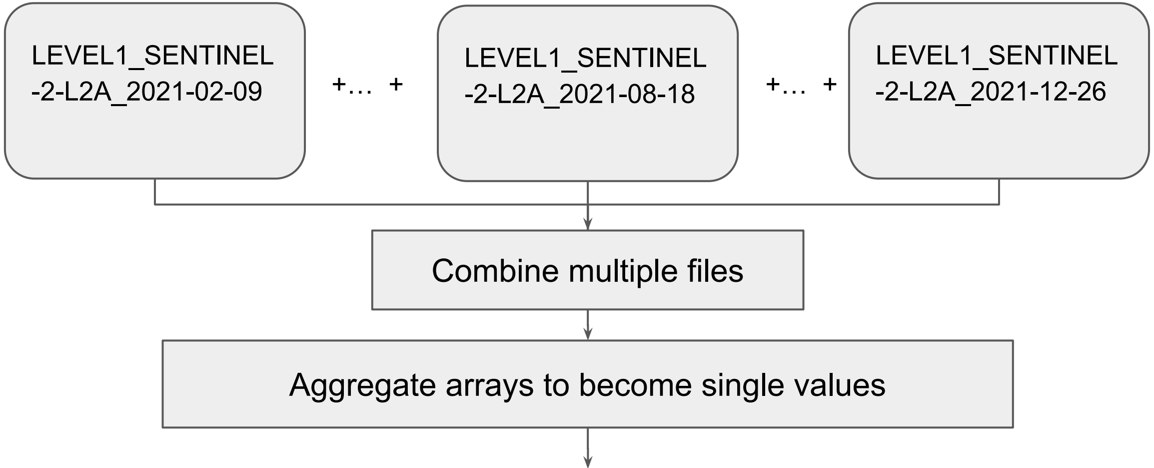


Each column indicates a particular column with specific wavelength band and window size, e.g. **B02_w5**:

- B02: wavelength band
- W5: window with width and height of 5 pixels

Each cell consists of an array for pixel values its respective band in the window as shown on the diagram on the left.

Data Preprocessing



B08_w5_0209	WVP_w5_0209	visual_w5_0209	B05_w5_0209	B06_w5_0209	B07_w5_0209	...	visual_w5_1226	B05_w5_1226	B06_w5_1226
4221.680176	4281.600098	36.240002	801.640015	3191.439941	4867.640137	...	239.919998	3530.320068	3488.919922
3028.879883	4149.000000	105.120003	1057.880005	2121.879883	2811.120117	...	75.279999	1011.520020	1087.719971
3925.439941	4665.959961	33.880001	629.200012	2336.879883	3412.000000	...	208.399994	2845.080078	2836.919922
5782.240234	4359.680176	44.599998	1049.520020	3931.879883	5937.359863	...	255.000000	5028.359863	4847.439941
6556.000000	4377.000000	254.240005	4123.359863	5969.799805	7028.799805	...	244.960007	4037.959961	3907.080078
...	...	...	...	...	...	...	...	...	...

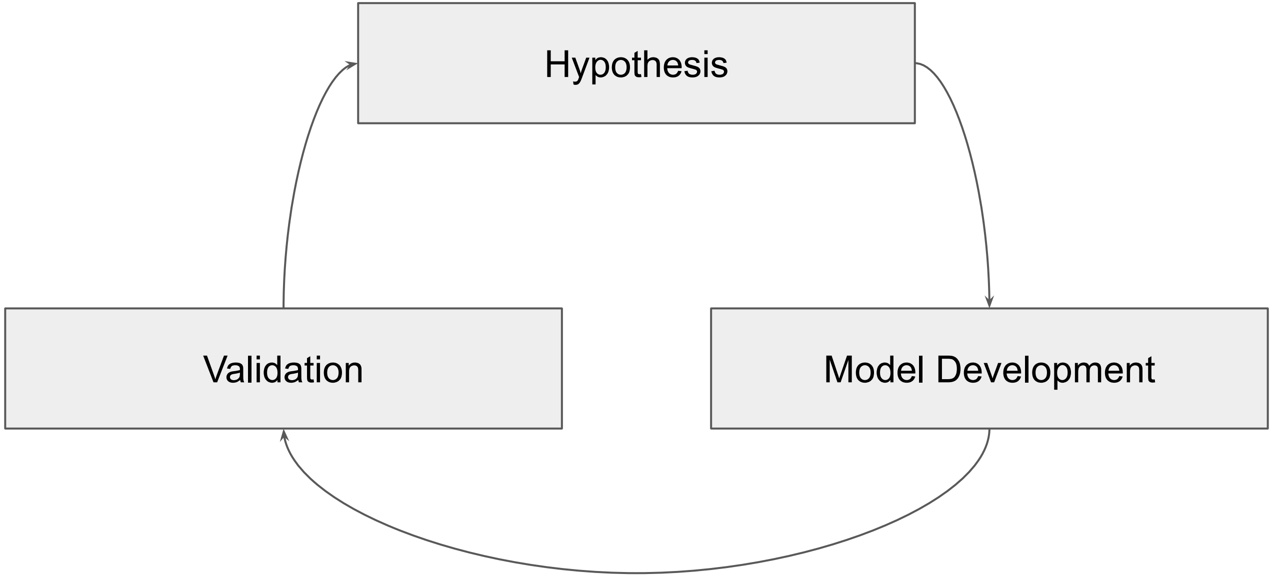
Sample of aggregated data.

Multiple files are combined and aggregated to include information from multiple wavelength bands and dates as data for model development.

sample of one particular column with specific wavelength, window size and date, e.g. **B02_w5_0209**:

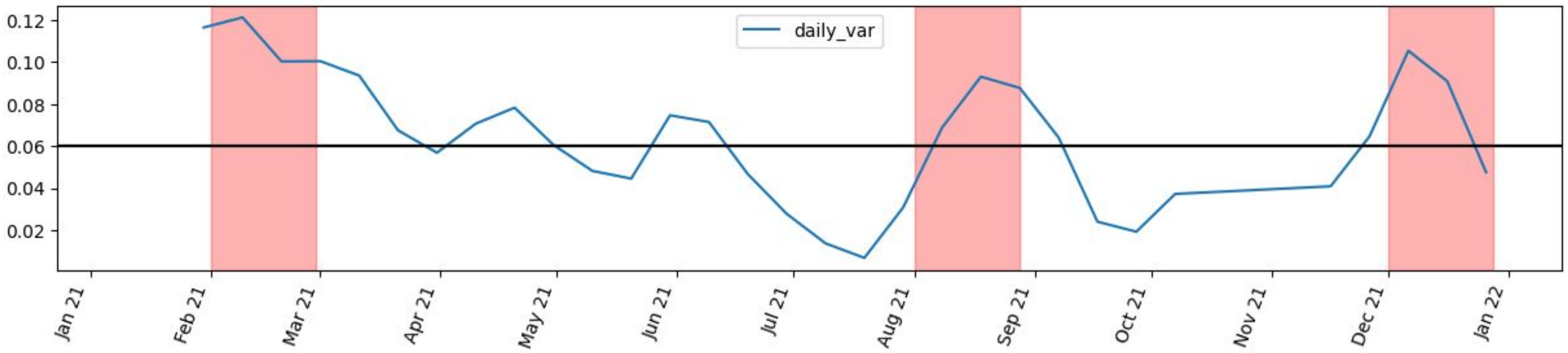
- B02: wavelength band
- W5: window with width and height of 5 pixels are aggregated into a single value with mean.
- 0209: date of which satellite data is collected

Model Development Experiments



Assumption 1: NDVI Variance in Cropping Season

In this case, we assume that **the color of rice during the cropping season is the greatest differentiator between rice field and the other land cover.** So, we selected data from the months with peaks in NDVI variance between rice fields and the other landcover, i.e. Februaru, August and December. As as baseline model, only Sentinel-2 data is used.   .



Evolution of Models + Test F1-scores

Based on the dataset queried based on the NDVI variance assumption, satellite data for February, August and December is used to develop classification models to predict the class of given coordinates

Iteration 1

test F1-score = 0.89

- Random Forest
- window size of 5*5, aggregated by mean

Baseline model.

Iteration 2

test F1-score= 0.86

- all February, August, December data + NDVI
- window size of 5*5, aggregated by mean
- remove highly correlated features
- stack models

From previous experimentation, we assumed that stacking models might lead to improved performance increasing robustness. However, model stacking reduces F1-score when tested against unseen test data. .

Iteration 3

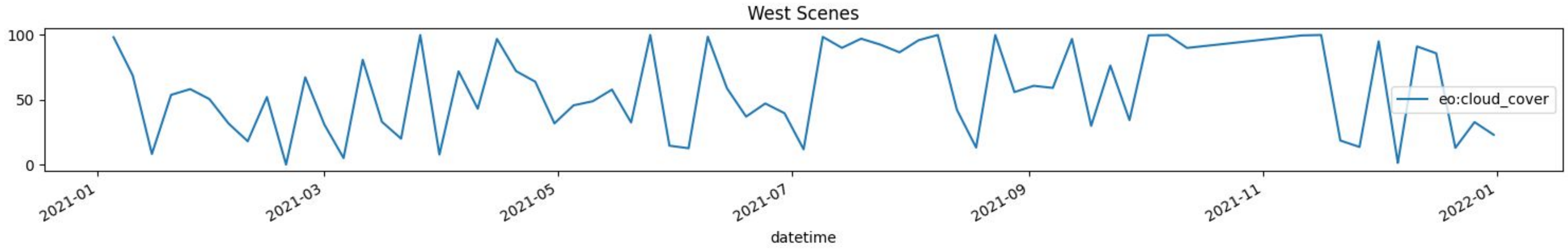
test F1-score= 0.95

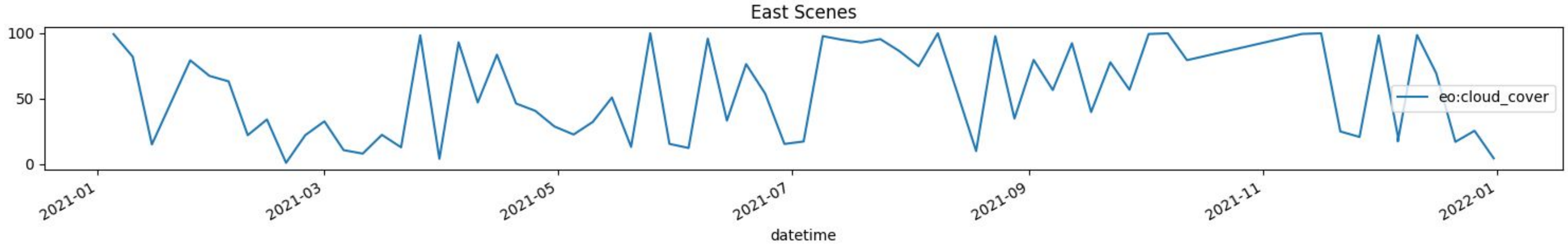
- Sentinel-2: Feb, Aug, Dec raw data + NDVI
- Sentinel-1: Sentinel-1 raw data data + vh/vv
- drop highly correlated features
- normalization and stack models

Adding Sentinel-1 data to the configurations used in iteration 2 improved model performance significantly. *New assumption: ability to remove the influence of cloud is the most important factor to increase model performance.*

Assumption 2: Cloud Removal

As we observe that the inclusion of Sentinel-1 data in `iteration 3` significantly improves our prediction accuracy, we assume that **<u>cloud removal is the most important factor in this classification task</u>**. We conduct cloud analysis and find out the dates with the least amount of cloud hanging over the training sample coordinates throughout the year. Based on the dates, we extract their corresponding Sentinel-1 and Sentinel-2 data. We increased window size to 9*9 to reduce the impact of possible cloud covering the window.





Evolution of Models + Test F1-scores

Iteration 4

Test F1-score = 1.0 !!!

- take sentinel-1 and sentinel-2 data with <15% cloud coverage directly over our training data
- window size: 9*9, aggregated by mean
- normalization (MinMaxScaler)
- apply random forest classification

Based on the conditions established, we realise that we achieved a perfect F1-score of 1.0.

Iteration 4.1

Test F1-score = <1.0

- take sentinel-1 and sentinel-2 data with <15% cloud coverage directly over our training data
- window size: 9*9, aggregated by mean
- normalization (MinMaxScaler)
- remove highly correlated features
- apply random forest classification

Trying to simplify the classification model, removal of some highly correlated features results in reduction in test F1-score.

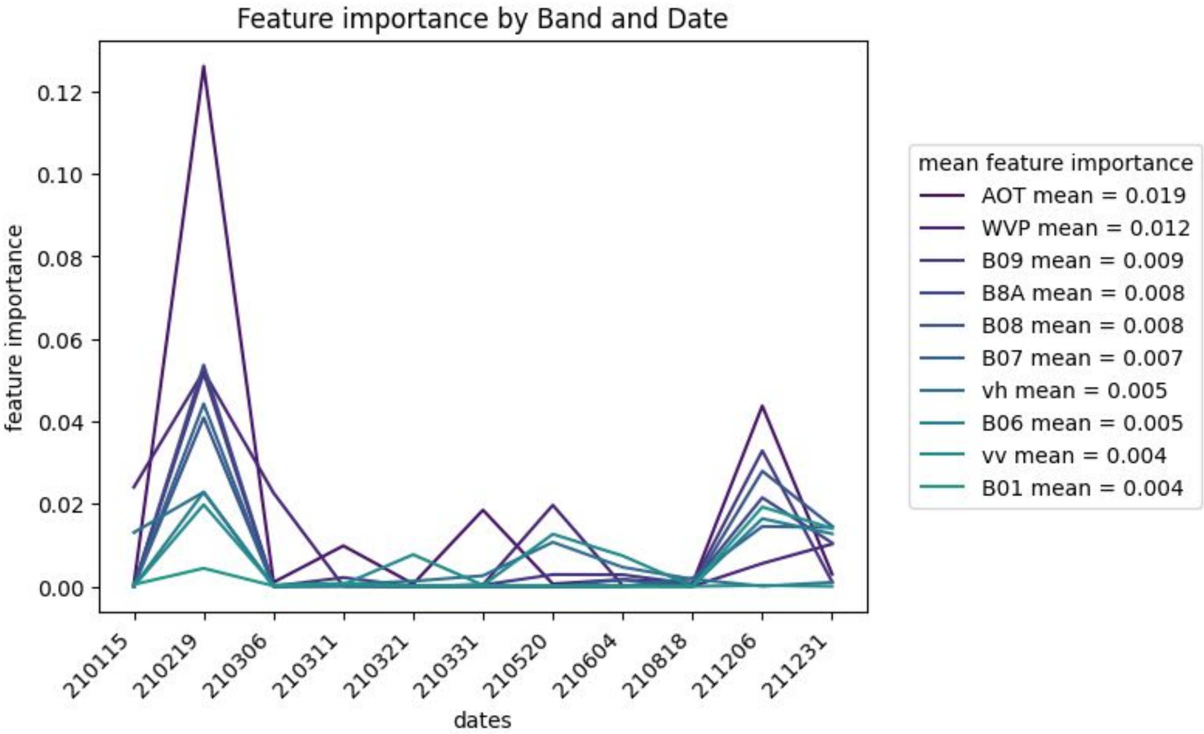
Iteration 4.2

Test F1-score = 1.0

- take sentinel-1 and sentinel-2 data with <15% cloud coverage directly over our training data
- window size: 9*9, aggregated by mean
- add NDVI and vh/vv features
- normalization (MinMaxScaler)
- remove highly correlated features
- apply random forest classification

By adding NDVI and vh/vv features to **iteration 4.1**, we achieve perfect F1-score of 1.0 again.

Highest Performing Features



Due to the large number of features and variation by time is involved, feature importance of the model is not easily interpretable.

In this case, we investigate the feature importance of each band for the dates chosen over the year. The plot shows the feature importances of the highest performing band over time.

Overall, ‘AOT’ and ‘WVP’ band have the highest average feature importance, but we notice that all bands have pretty small feature importance.