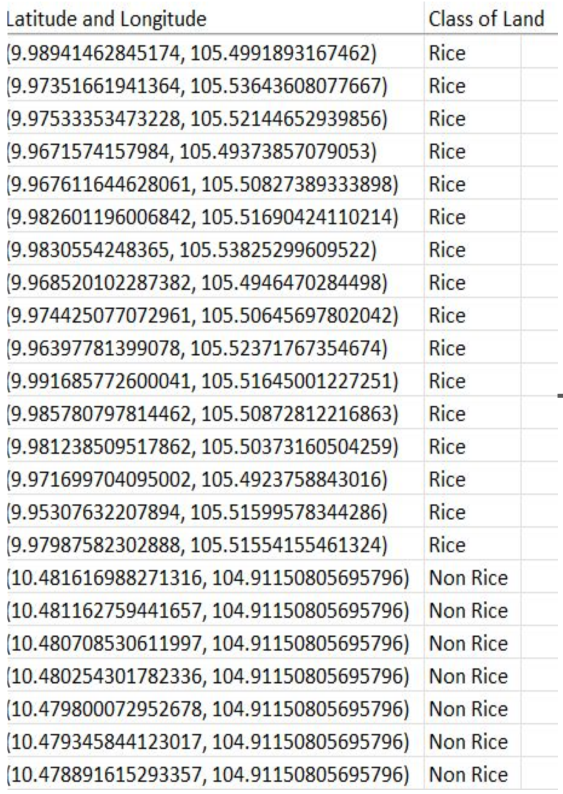
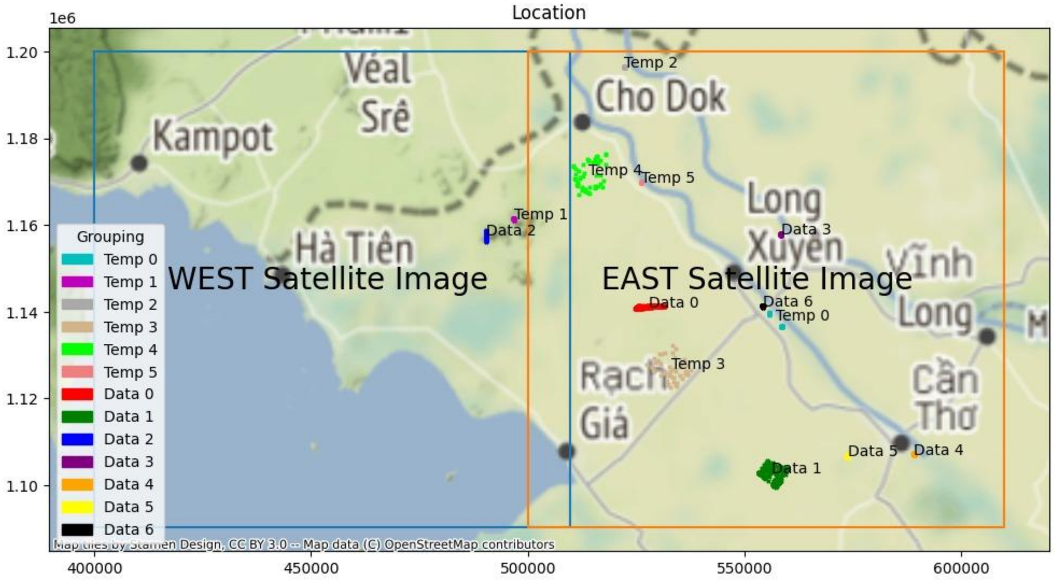
2023 EY Open Science Data Challenge - Level 1

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 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 stac API with Python.

Range of Dates: Jan 2021 - Dec 2021

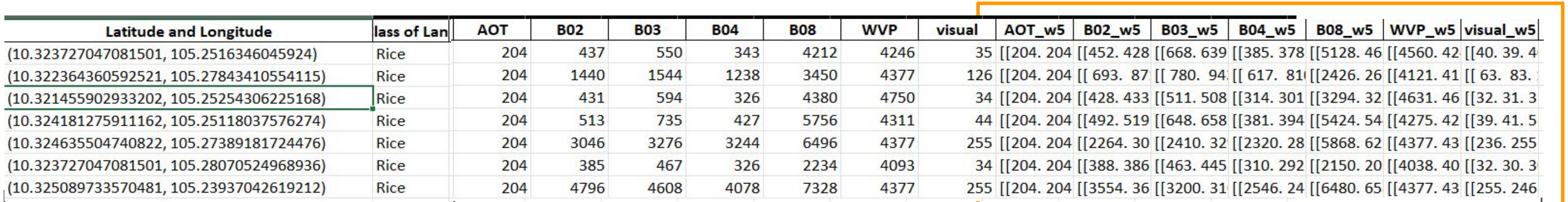
Data Sources

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 visually but unable to penetrate cloud)

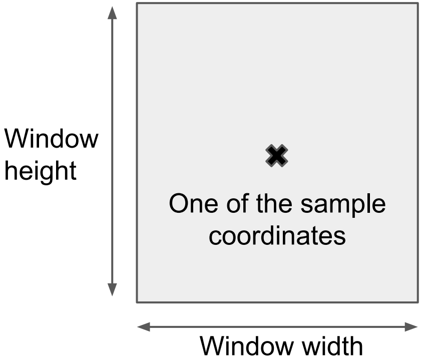
Collected Data

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

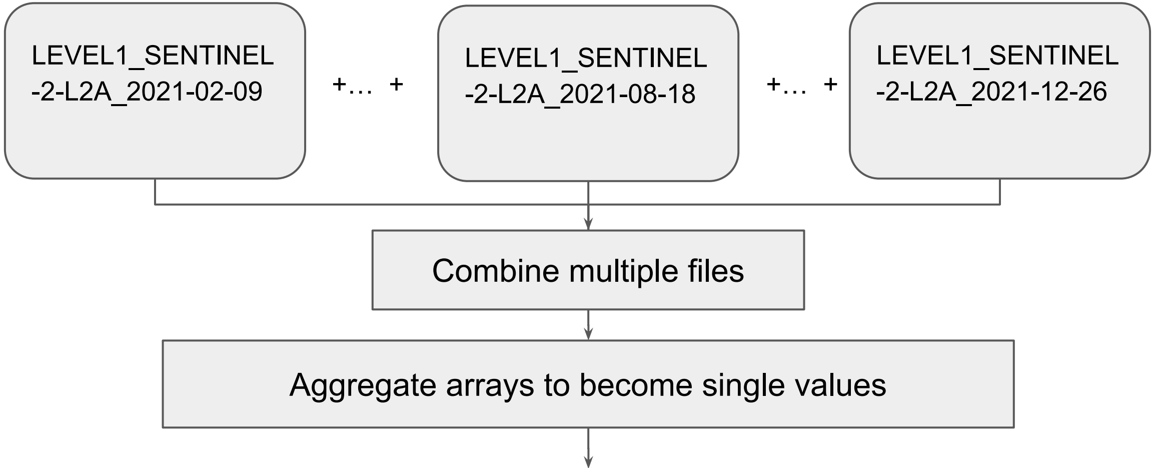


Each column indicates a column with specific wavelength band and window size, e.g. **B02_w5**:

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

Each cell consists of an array of pixel values for its respective band and coordinate in the window.

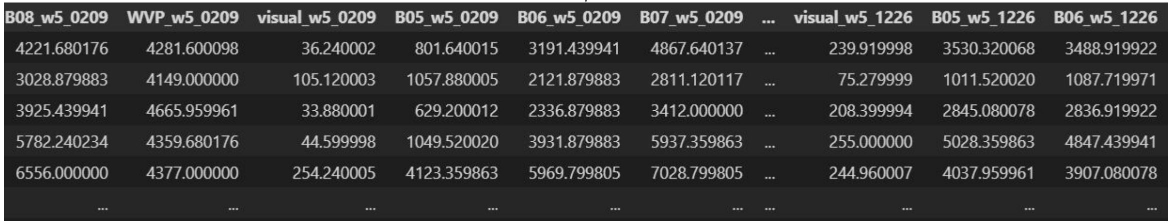
Data Preprocessing



LEVEL1_SENTINEL-2-L2A_2021-02-09 +… + LEVEL1_SENTINEL-2-L2A_2021-08-18 +… + LEVEL1_SENTINEL-2-L2A_2021-12-26

Combine multiple files

Aggregate arrays to become single values



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.

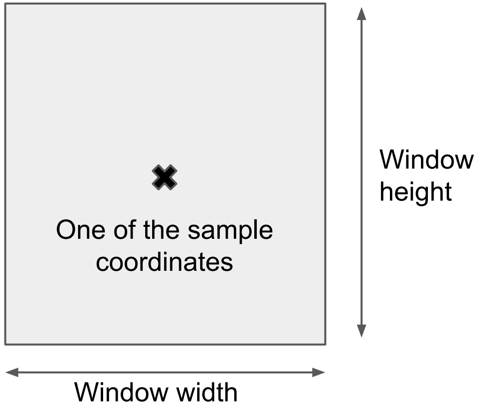
Multiple files are combined and aggregated to include information from multiple wavelength bands and dates as data for model development.

Each column contains data with specific wavelength, window size and date, e.g. **B02_w5_0209**:

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

Input data is in a structured table format.

Preprocessed Data



One of the sample coordinates

Window height

Window width

X 600 data points

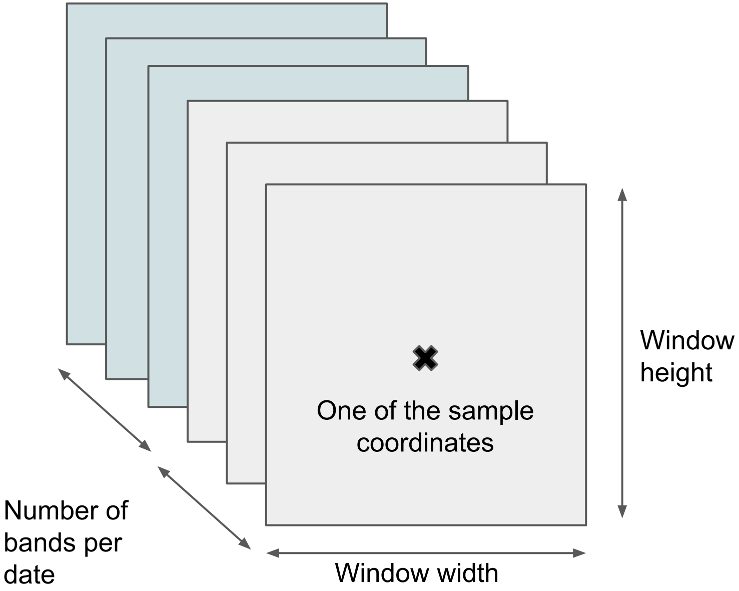
The diagram above shows a sample of one particular column with specific wavelength, window size and date, e.g. **B02_w5_0209:**

wavelength

The collected satellite data goes through a series of transformation. The processed data used to train the predictive model has a tensor data structure as illustrated in the diagram on the left.

- X in the diagram represents each coordinate
- The amount of contextual spatial information to include is decided by the window width around the coordinate.
- Each slice of array represents data from a specific band / wavelength
- Arrays from different dates are stacked to provide extra information about the sample coordinate.

Preprocessed Data



The diagram above shows the feature window extracted from satellite data for a sample coordinate.

The collected satellite data goes through a series of transformation. The processed data used to train the predictive model has a tensor data structure as illustrated in the diagram on the left.

- X in the diagram represents each coordinate
- The amount of contextual spatial information to include is decided by the window width around the coordinate.
- Each slice of array represents data from a specific band / wavelength
- Arrays from different dates are stacked to provide extra information about the sample coordinate.

Model Development Experiments

Insight 2: Adding more dates as features will improve model performance (until they overfit)

Using the same set of machine learning models, adding more dates as features improve the performance of features. This fits our common sense as crops go through multiple cycles throughout the year and more sampled dates result in more useful features informing the prediction model.

In our case, we study this by setting a set of number of dates sampled to be used as our predictive features, i.e. 1 day, 2 days, 1 month, 3 months, 4 months. The accuracy of models increase as we added more dates as features. However, we do not use all available dates throughout the year to avoid overfitting as we only have 600 training samples.

Insight 3: For the same input data, different model can show very different prediction.

Performance of each model fluctuates and one do not show consistent advantage over the other. It shows that model stacking might be able to help to make the model prediction to become more robust.

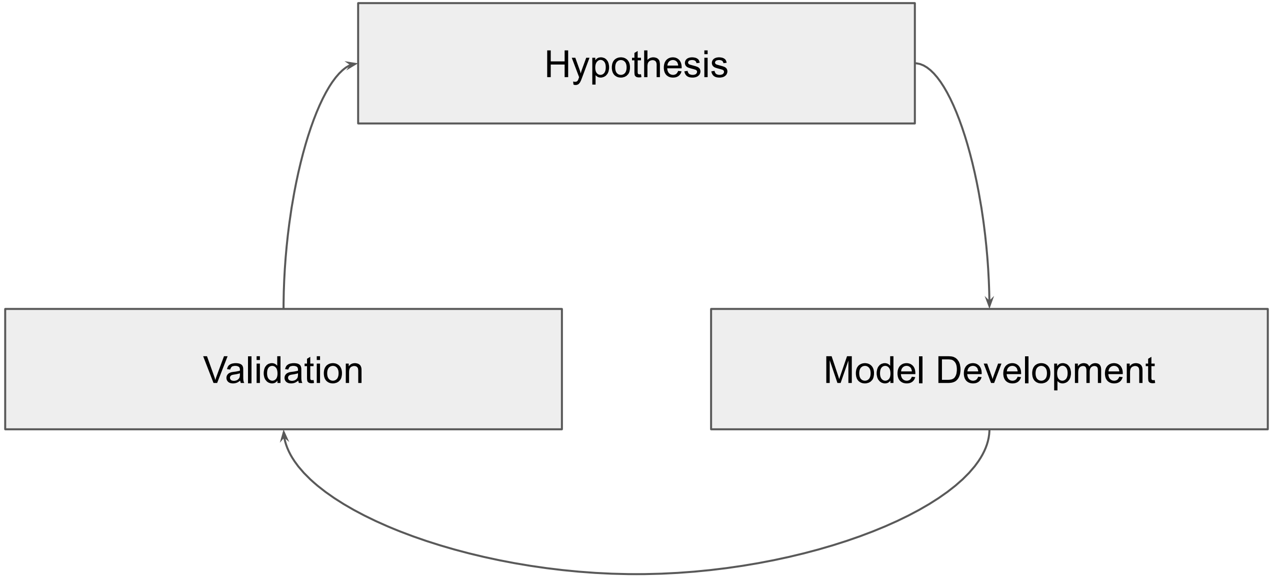
Model Development Experiments

Limitations of experiments

Due to the training samples being highly similar with one another and are not random enough, most of the experiments return F1-score very close to 1.0 when evaluated via cross-validation. This makes us being unable to see significant improvements or drop in f1-score with cross-validated evaluation. Thus, there are multiple explorations done but do not provide any valuable lessons for model development and many more experiments are needed to be validated against unseen test data, e.g.

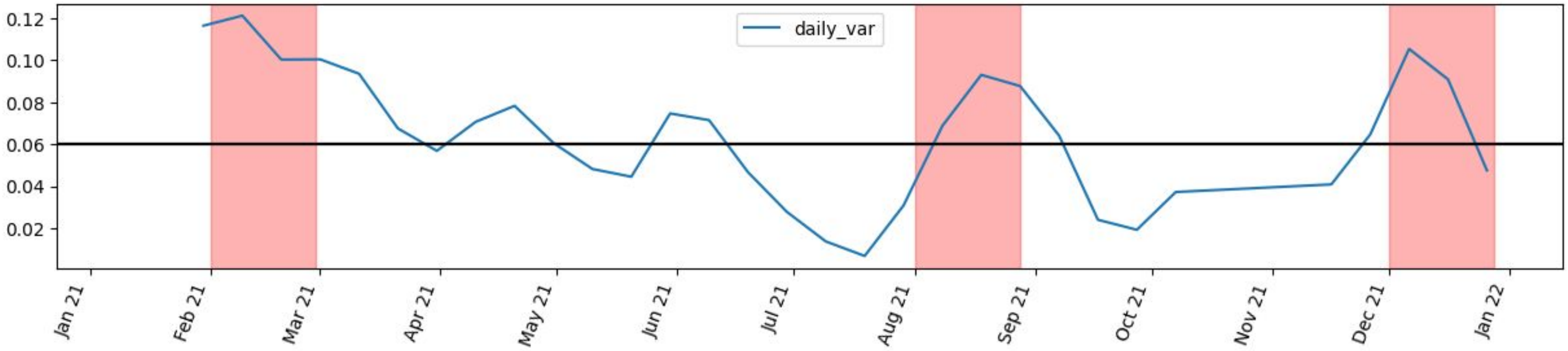
- model stacking
- hyperparameter tuning
- feature selection by removing highly correlated values
- generate NDVI for each date
- adding Sentinel-1 data ('vv', 'vh', 'vv/vh')

Model Development Experiments



Assumption 1: NDVI is the most important differentiator

In this case, we assume that **the density of greenness of earth surface is the most important differentiator between different land covers.** So, we selected data from the months with peaks in NDVI of rice fields compared with the average NDVI of all land covers, i.e. February, August and December. .



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

- Only Sentinel-2 data
- 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

We assumed that stacking models + extracting NDVI might lead to improved performance increasing robustness. However,this approach reduced the F1-score when tested against unseen test data. *These typical approaches are not the key to improve model performance.*

Iteration 3

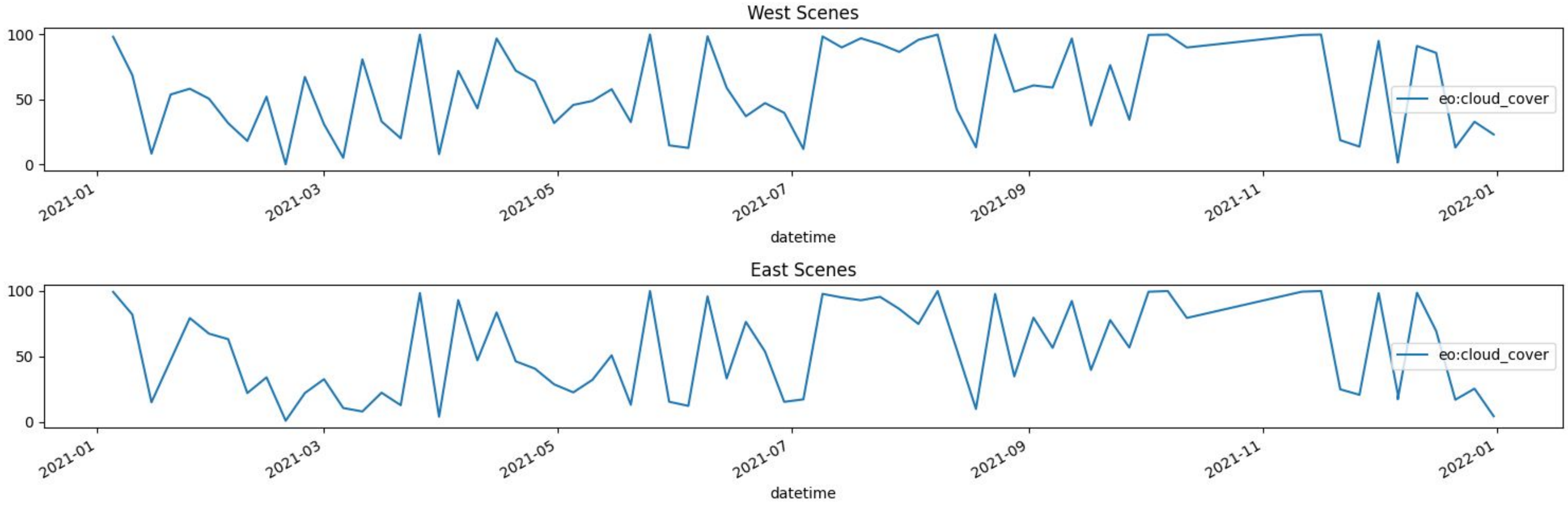
test F1-score= 0.95

- 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 **cloud removal is the most important factor in this classification task**. 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.

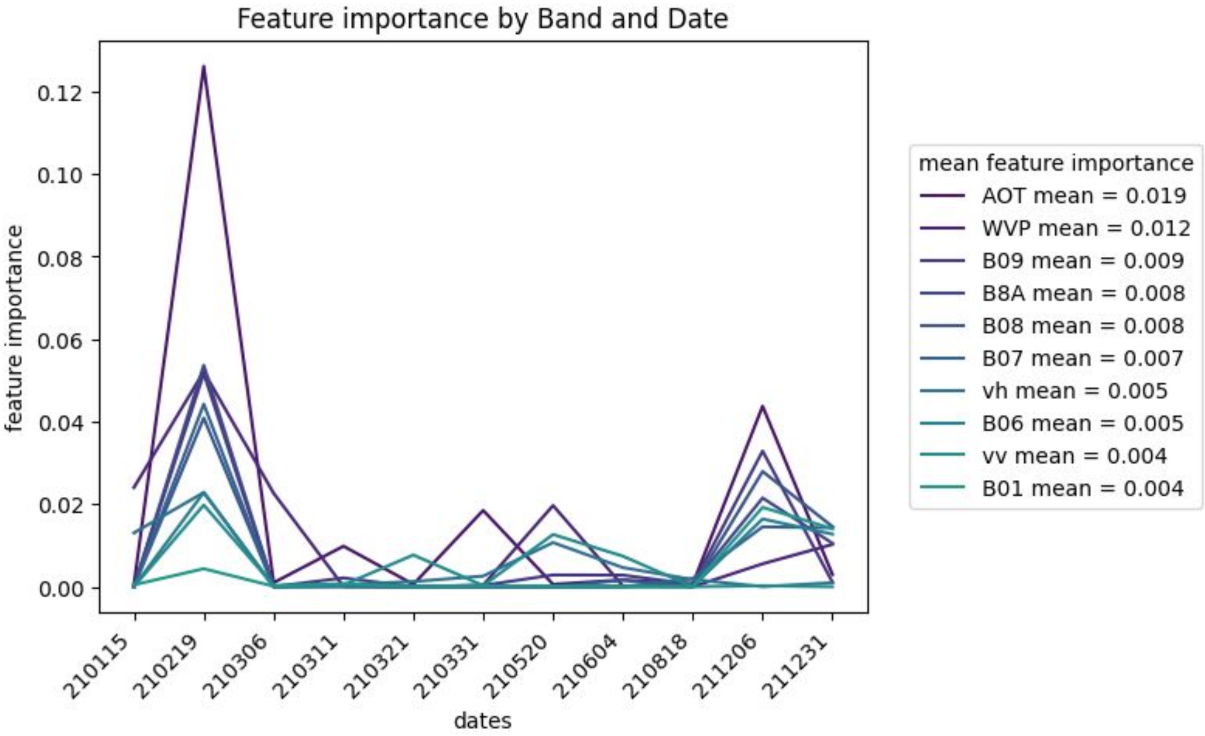
Iteration 4.2

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.