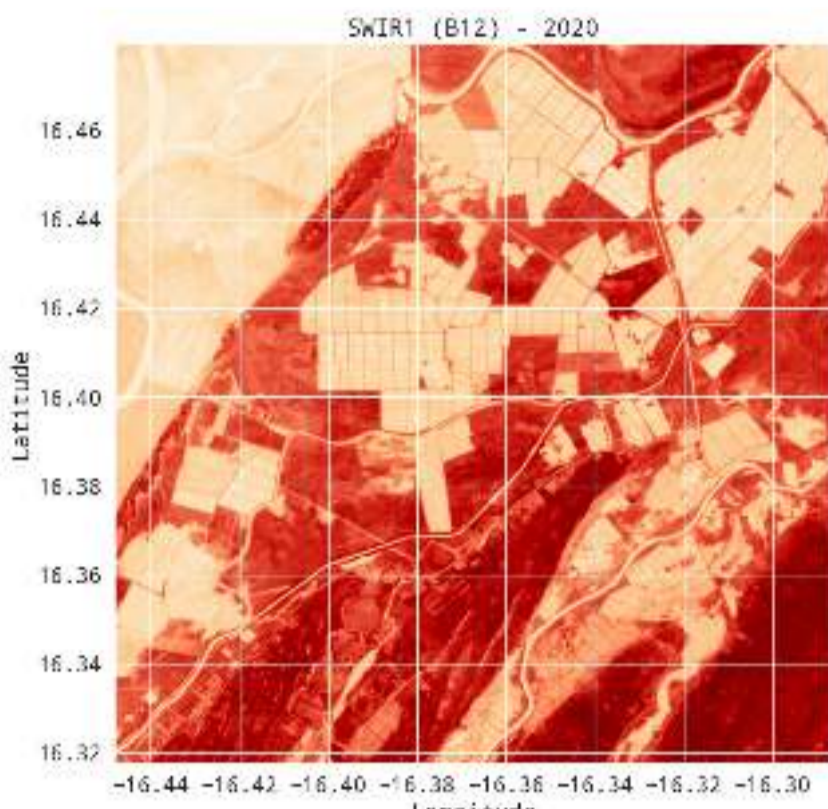


Identifying Rice Cropping Practices In The Senegal River Valley Post-Intervention Using Sentinel-1/-2

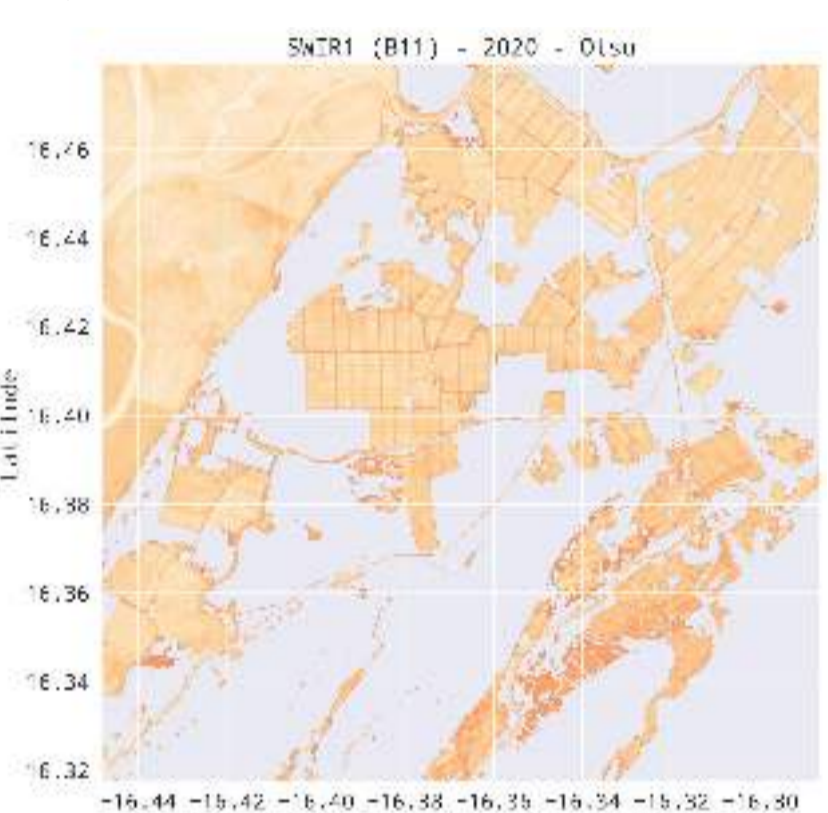
*D. Ó Fionnagáin^{1,3}, R. Trearty^{1,3}, Jemima O'Farrell^{1,3}, Yared Tessema^{2,3}, Michael Geever^{1,3}, Patricia Codyre^{2,3}, Charles Spillane^{2,3}, Aaron Golden^{1,3}

¹School of Natural Sciences, ²School of Biological & Chemical Sciences, ³Ryan Institute College of Science and Engineering, University of Galway, Galway, Ireland, H91 TK33
[†]dualta.ofionnagain@universityofgalway.ie

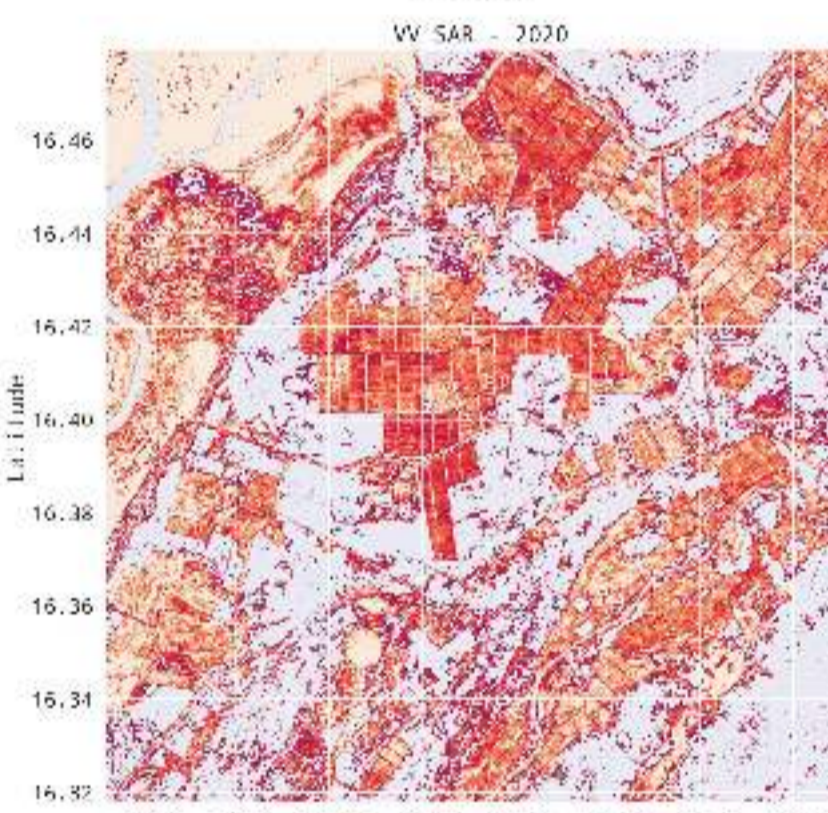
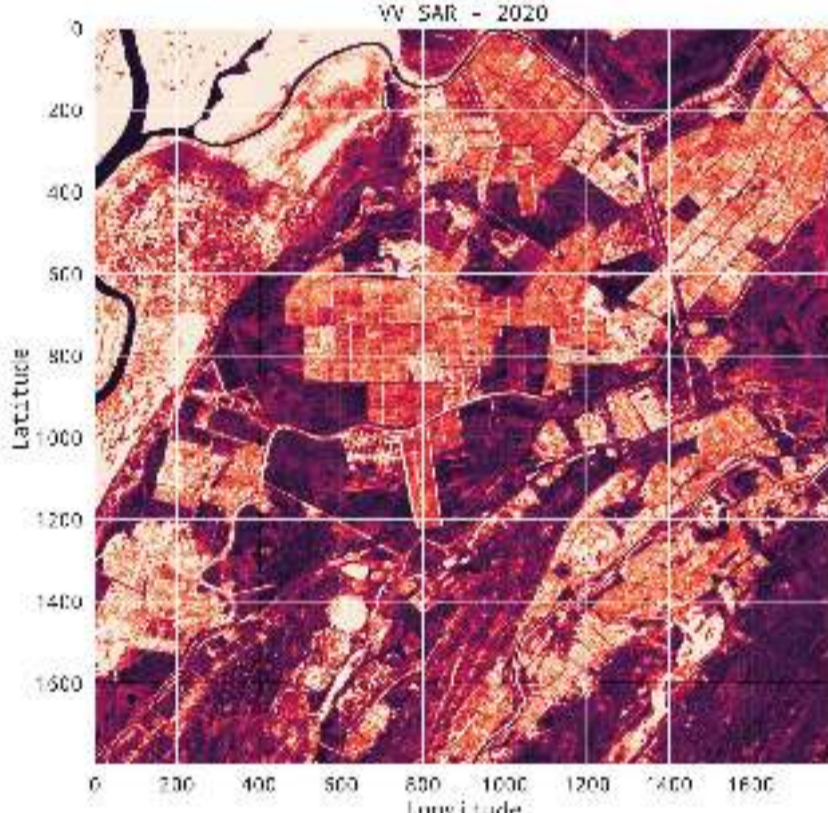
Data Processing Workflow Example



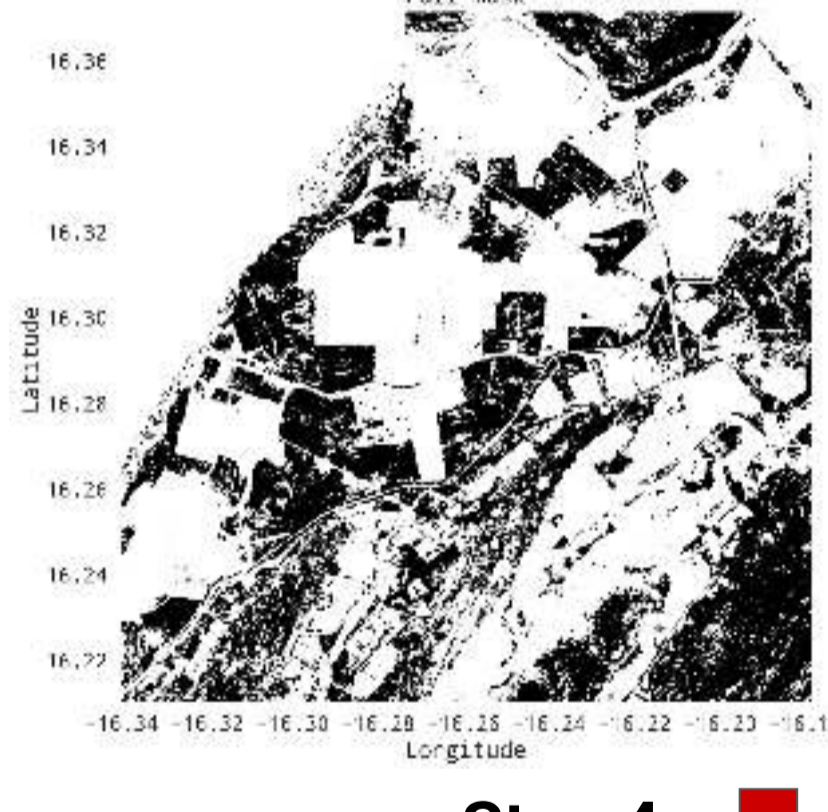
Step 1: Otsu thresholding of SWIR data. Taking advantage of strong response of vegetation in IR. Works very well in dry arid conditions.



Step 2: Repeat for SAR data (VH and VV)

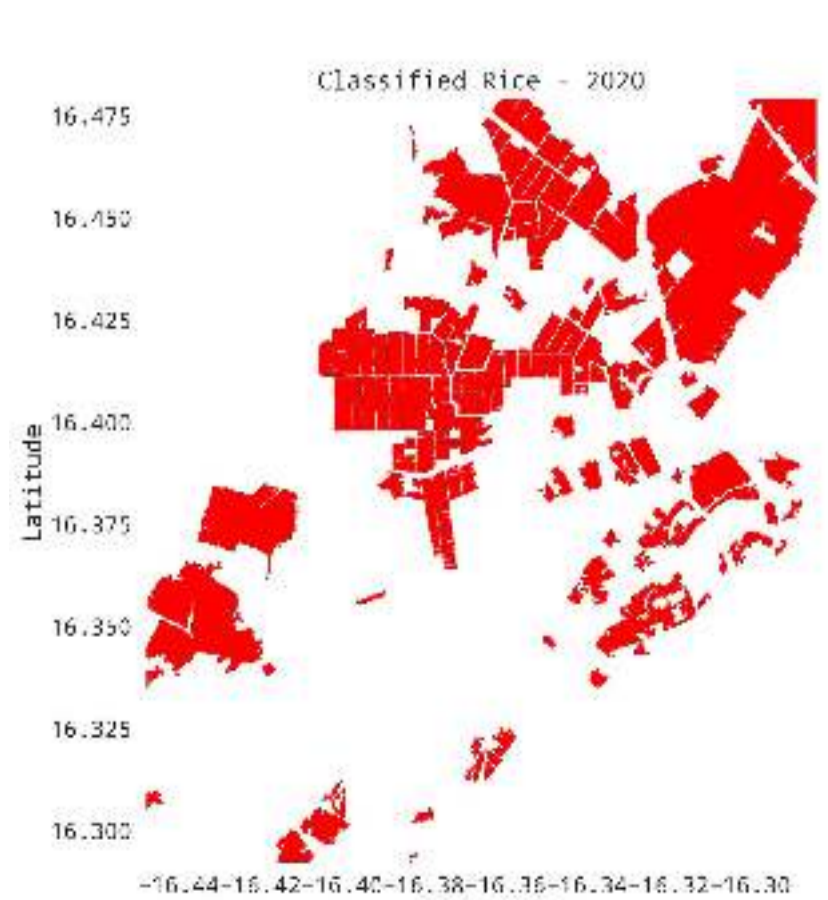


Step 3: Combine masks.



Step 4: Run masked data through AI models (section 2).

Step 5: Sieve resulting classified pixels to 20 hectare minimum.



Step 6: Use rice crop mask to analyse farming practices in the SRV using other EO metrics.

1 Identifying Changes in Cropland use Dynamically

The Senegal River Valley region has been a focal point for the intervention of NGOs for decades, with hundreds of millions of dollars being spent^{1,2,3} to stabilise and improve its rice crop productivity given that it is a high-risk area for the impact of climate change and desertification. Global crop masks perform very well in well-studied geographic locations from space, but fail to classify croplands in other regions of the globe. The ESA WorldCover land cover map works well in Europe but fails in sub-Saharan Africa⁴.

Complicating the issue is the dynamic nature of tillage farming. Farmers may choose to change crop season-to-season based on the fluctuating markets and gate prices⁵. Figure 1 shows the changes in cropping between 2020 and 2022. Here, we are studying the growth of rice in northern Senegal, particularly in the Senegal River Valley (SRV) and the river delta. We implement a multi-classification model on each growing season to determine total cultivated areas between 2019 and 2022 in the region.

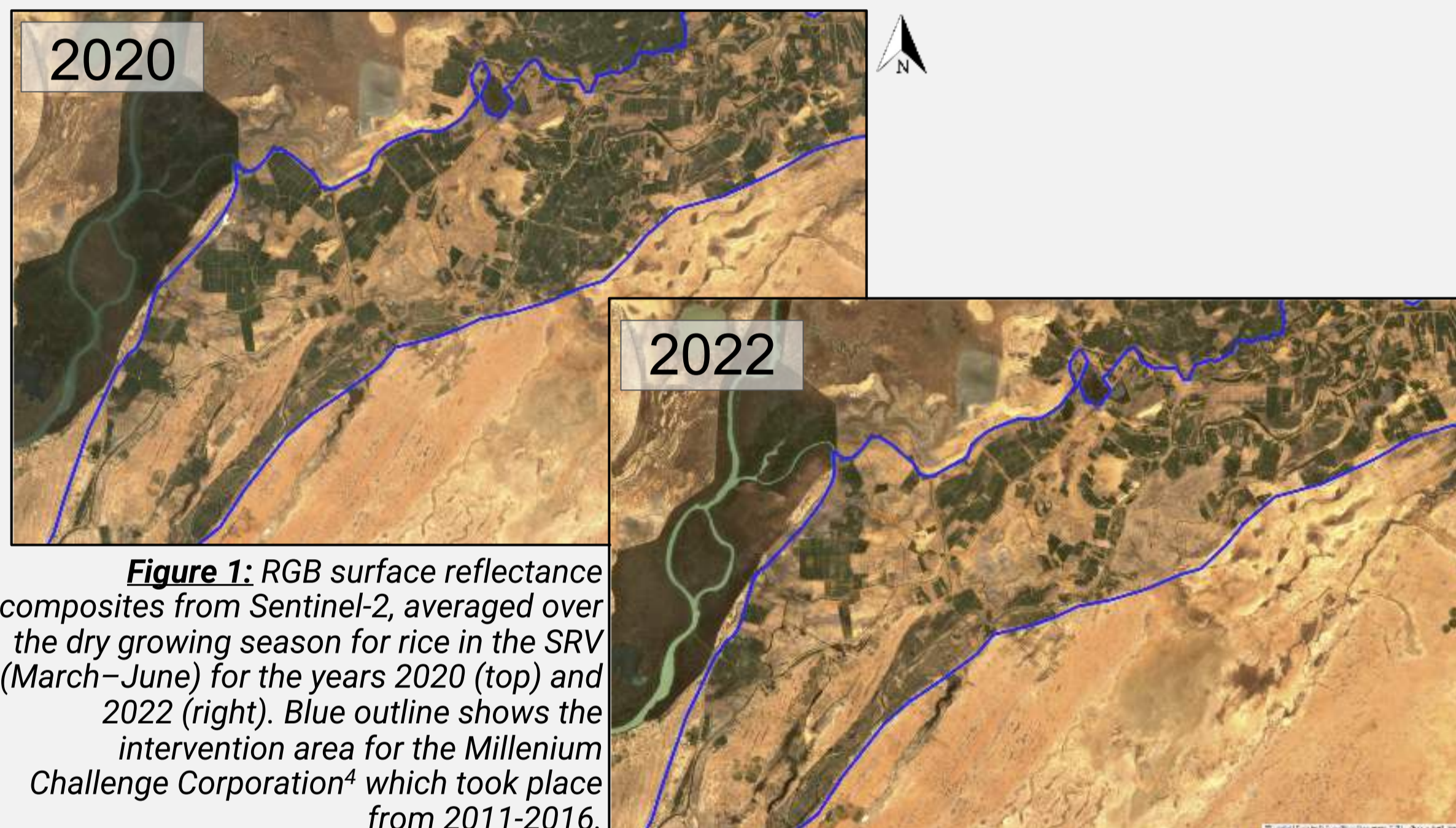


Figure 1: RGB surface reflectance composites from Sentinel-2, averaged over the dry growing season for rice in the SRV (March-June) for the years 2020 (top) and 2022 (right). Blue outline shows the intervention area for the Millennium Challenge Corporation⁴ which took place from 2011-2016.

3 Measuring Crop Cycles and Intensification Through Time-series to CNN Classification

The phenological cycle of rice can be mapped using 3 satellite signals, Enhanced Vegetation Index (EVI), Normalized Difference Yellow Index (NDYI), and VH polarization, Fig 4⁷ shows how each of these signals behave through the course of the crop cycle.

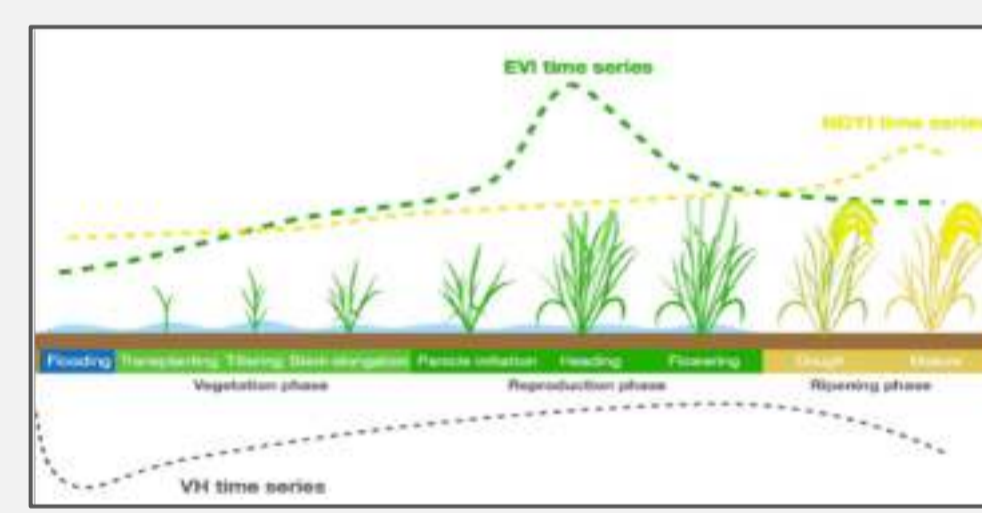


Figure 4: The Phenology of rice tracked by EVI, NDYI and VH⁷

These three signals were extracted from the Sentinel-1 and Sentinel-2 earth observation platforms using crop-masks generated using the methods outlined in panel 2 for the cultivated regions under scrutiny. This results in time series for each of the three indices for each pixel, with every pixel having ~10 m spatial resolution. These time series are then smoothed⁸ and converted to polar coordinates before we apply the Gramian Angular Field (GAF) transformation to each time series creating a Gramian matrix. This matrix is then used to create a unique image for each index's time series. A colour channel is assigned to each index resulting in three monochromatic images, EVI as green, NDYI as red and VH Polarization as blue. These three images can then be combined into a single RGB image capturing the time series for all three indices in one unique image for that site for that year. With these labelled images we can train a simple Convolutional Neural Network to classify the each site into one of three classes, Double Cropped, Single Cropped and Fallow. This trained CNN can then be used to classify each site from a crop-mask for each year showing how intensely sites are being farmed.

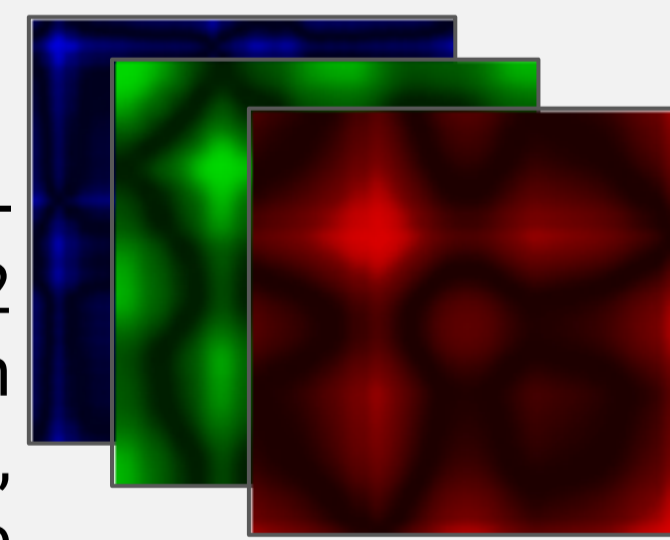


Figure 5: The Monochrome images representing each Time series for a double cropped site.

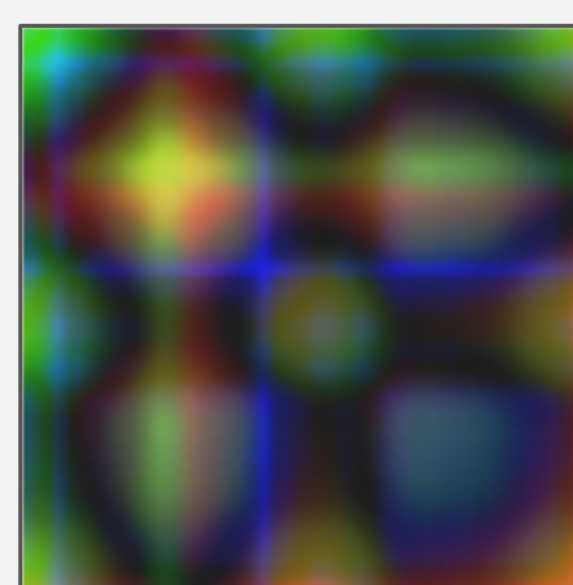
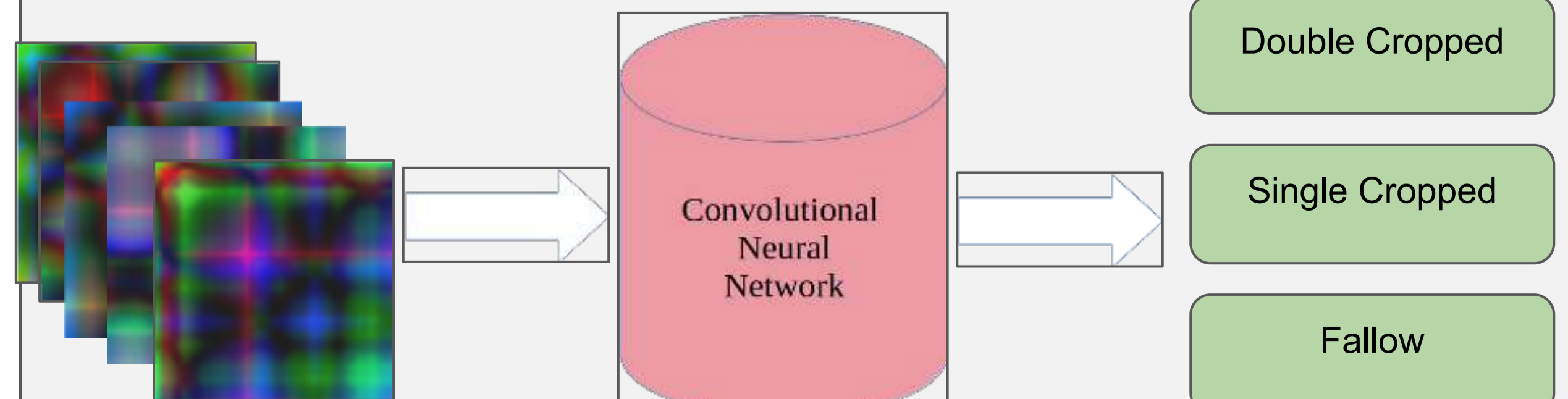


Figure 6: The final combination of each monochrome image into one unique RGB image representing the rice growth pattern over a year for one Double Cropped site.



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- Senegal River Valley Rice - 20140560, 8 Dec 2014, *European Investment Bank*
- Senegal's IWRM Project at Five Years Post-Compact: Findings from a Mixed-Methods Evaluation, Harris et al., *Mathematica*, 2021
- Senegal River Valley Irrigated Rice Farming Improvement Project: Final Report, JICA, 2019
- Considerations for AI-EO for agriculture in Sub-Saharan Africa, akalembe & Kerner, 2023 *Environ. Res. Lett.* 18 041002
- Grain and Feed Annual Report - Senegal SG2022-0006, USDA/GAIN, 2022, [https://www.fas.usda.gov/data/senegal-grain-and-feed-annual-](https://www.fas.usda.gov/data/senegal-grain-and-feed-annual-6)

2 Ensemble Classification of Rice Croplands in SRV

We use multi-model classification of seasonal averaged Sentinel-1 and Sentinel-2 data. Masked and pre-processed data was used to manually label training data. Five classes were predicted in each of the four models (Random Forest, Naive Bayes, Multinomial Logistic Classification-MLC, and XGBoost), these are Rice, Flooded Rice, Water, Wetlands, and Other. Otsu masking⁶ results in mostly vegetation, water and wetlands left to classify in the data.

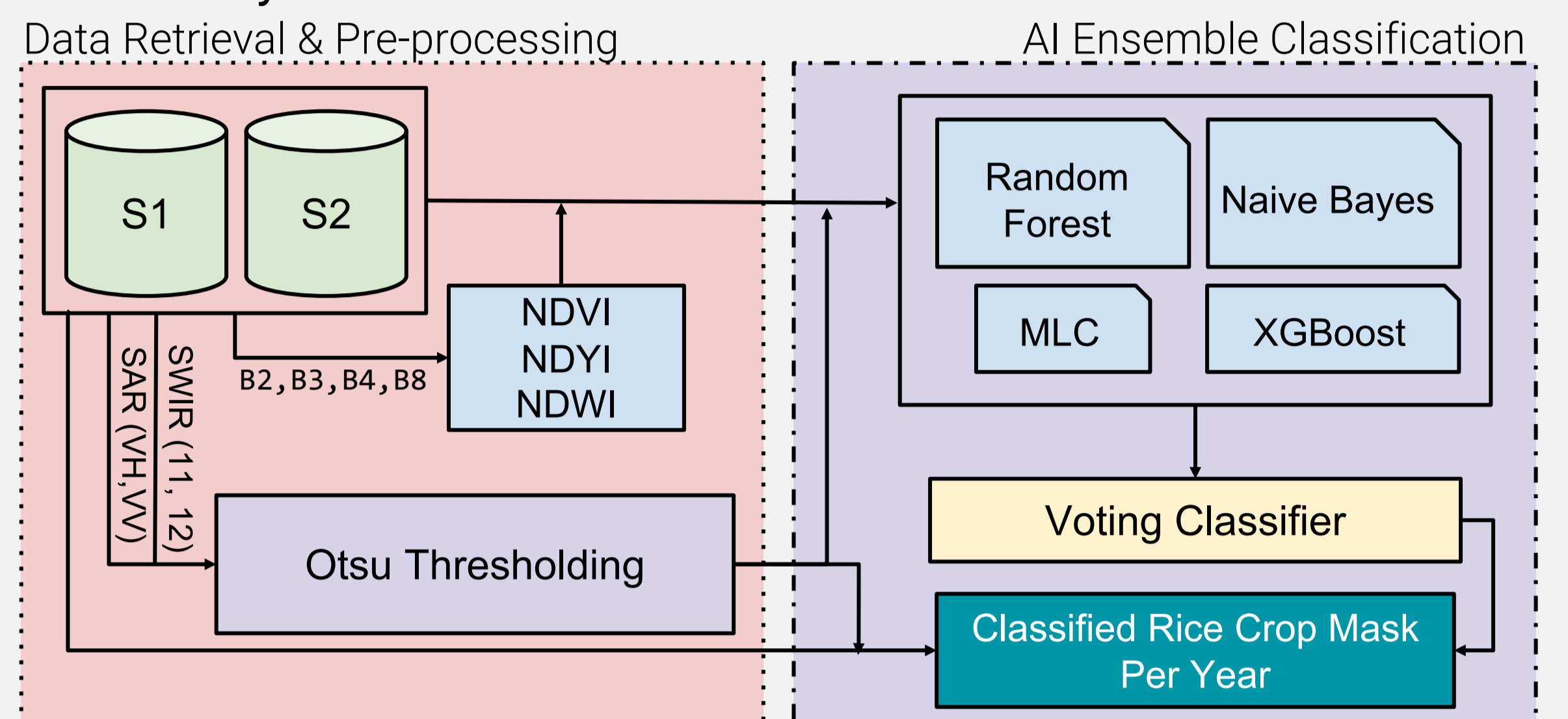


Figure 2: Sentinel-1/-2 data is retrieved from Google Earth Engine (COPERNICUS/S1_GRD & COPERNICUS/S2_SR_HARMONIZED), extra indices are calculated for the models (NDVI, NDYI, NDWI). Manually labelled data from these sources is then fed into the models for training. This output is aggregated in a voting classifier, which produces a rice classification mask.

Results from these four models are aggregated by a voting classifier. Figure 3 shows examples of classification of rice and calculated cultivated area for each year from 2019 to 2022.

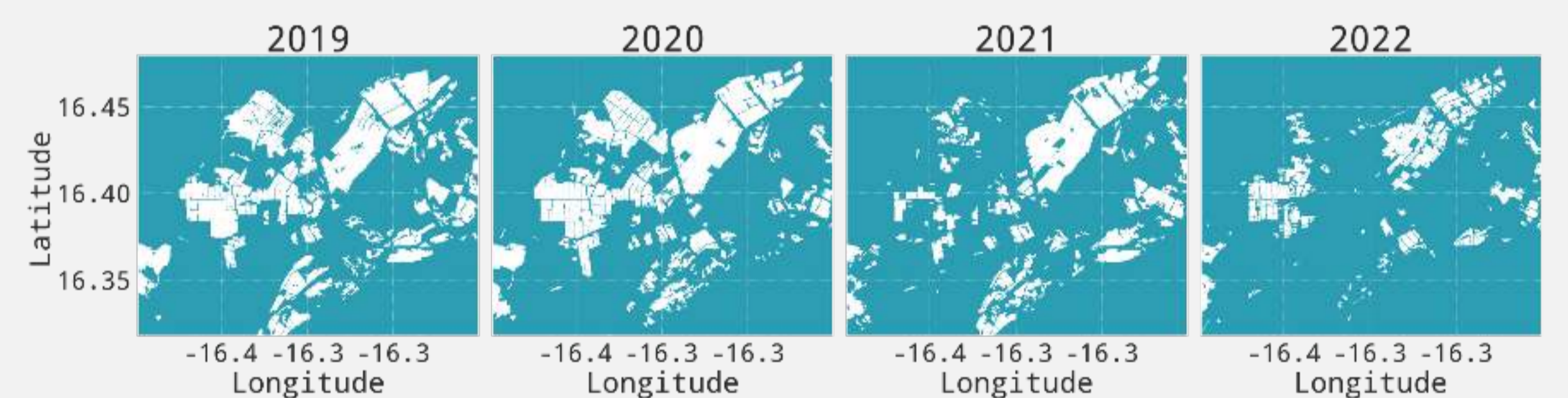


Figure 3: Rice cropland classified by the aggregated voting classifier for years 2019-2022. This shows a stark decline in cropped rice in the hot season (March-June) for these years.

4 Utilising These Tools to Measure Resilience and Adaptation to Climate Change



Figure 7: RGB image of the selected case study area.

A case study area was selected in the Senegal River Valley to which the classification methods were applied. The crop patterns for the years 2019, 2020, 2021 and 2022 were classified. Both the GAF/CNN classification and the NDWI signal show a clear overall trend of reducing rice cultivation and a significant reduction in double crop rice over the four years.



Figure 8: Rice crop pattern as classified by the GAF and CNN method.

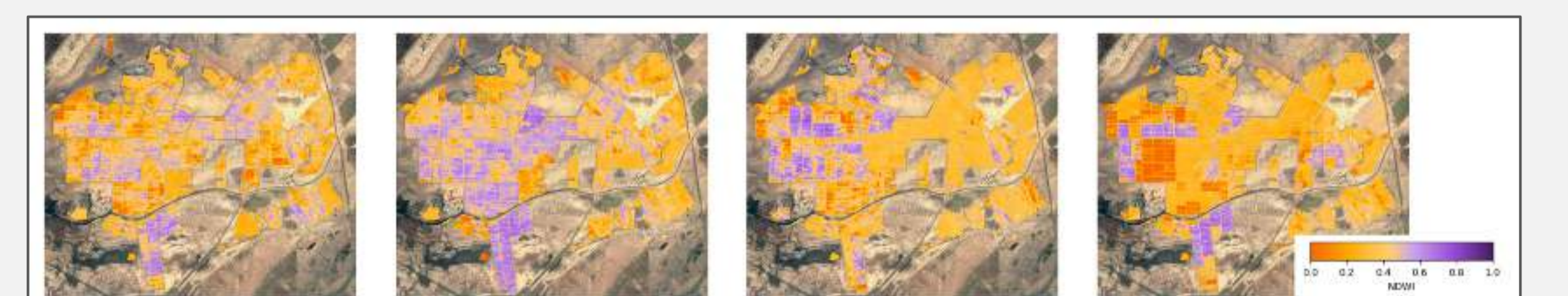


Figure 9: Normalised Difference Water Index (NDWI) for the case study region

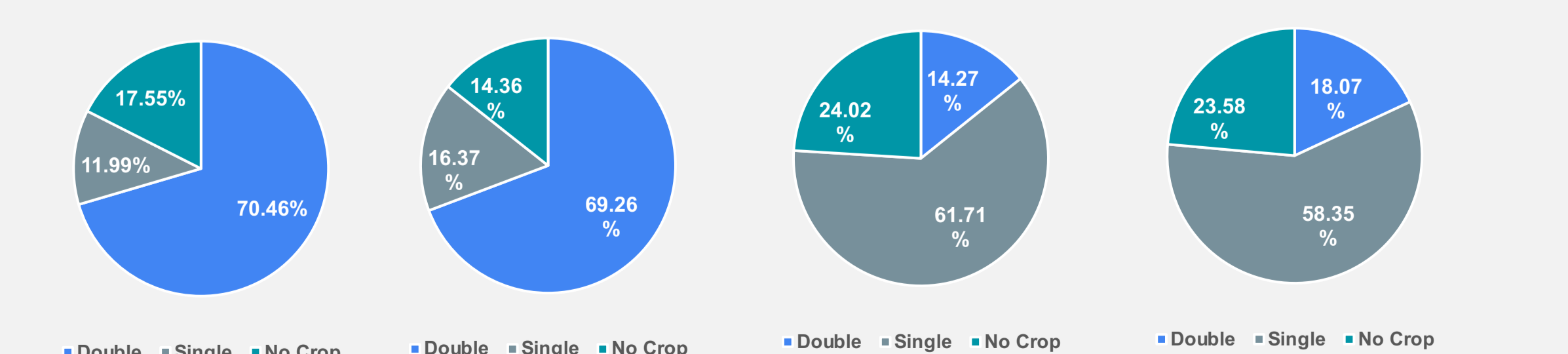


Figure 10: Percentage of double crop (blue), single (grey) and no crop (green) rice for the years 2019, 2020, 2021 and 2022.

⁶ "A Threshold Selection Method from Gray-Level Histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, N. Otsu, 1979
⁷ Feature-based algorithm for large-scale rice phenology detection based on satellite images, *Agricultural and Forest Meteorology*, 329, p. 109283. Zhao, X. et al. (2023).
⁸ Cappellari, M. (no date) loess: LOESS: smoothing via robust locally-weighted regression in one or two dimensions.
⁹ Multivariate Time Series Data Transformation for Convolutional Neural Network, *IEEE/SICE International Symposium on System Integration (SII)*, Yang, C.-L. et al. (2019)