# Integrating radar and multi-spectral data to detect cocoa crops: a deep learning approach

Adele Therias

FIRST SUPERVISOR Dr. Azarakhsh Rafiee

SECOND SUPERVISOR
Dr. Stef I hermitte





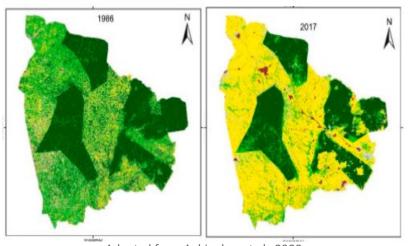
COMPANY SUPERVISOR Philip van der Lugt

CO-READER
Dr. Roderik Lindenbergh



# **MOTIVATION**

### **DEFORESTATION**



Adapted from Ashiagbor et al., 2022

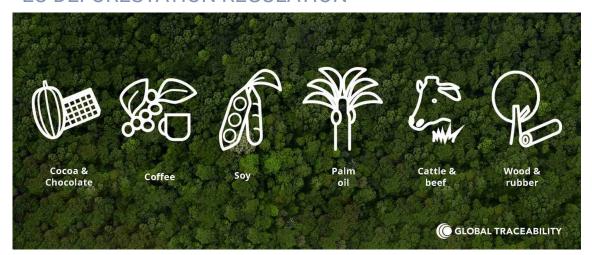
# 7.54% of EU-driven deforestation

### **COCOA PRODUCTION**



Meridia, 2020

### **EU DEFORESTATION REGULATION**



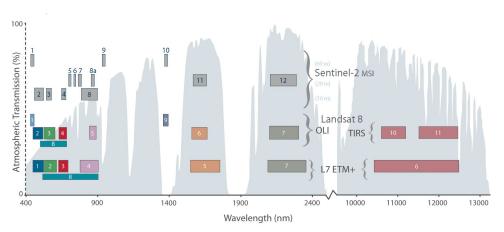
### **DETECTION CHALLENGES**



Satellite data: Google Earth accessed via QGIS XYZ tiles layer connection | Polygon data: Meridia B.V.

# MULTISPECTRAL IMAGERY

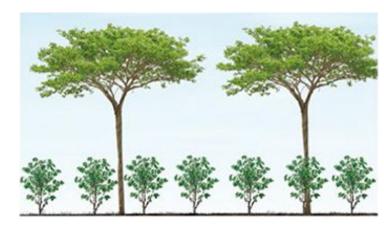
### MULTISPECTRAL IMAGERY



NASA 2015

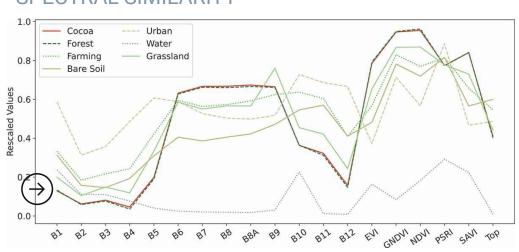
WEkEO, 2020

### MONOCROP CANOPY



Adapted from Orozco-Aguilar et al., 2021

### SPECTRAL SIMILARITY



Batista et al., 2022

### **VEGETATION SIMILARITY**





Google Earth accessed via QGIS XYZ tiles layer connection

# MULTISPECTRAL IMAGERY

### INTERCROP FARMS

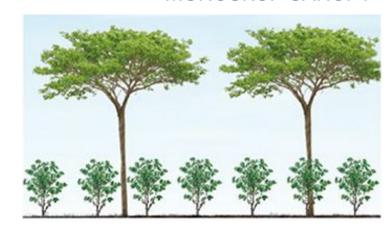


Google Earth accessed via QGIS XYZ tiles layer connection

### **AGROFORESTRY**

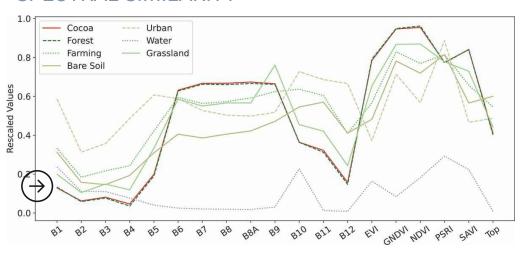


### MONOCROP CANOPY



Adapted from Orozco-Aguilar et al., 2021

### SPECTRAL SIMILARITY







**VEGETATION SIMILARITY** 

Google Earth accessed via QGIS XYZ tiles layer connection

Batista et al., 2022

# MULTISPECTRAL IMAGERY

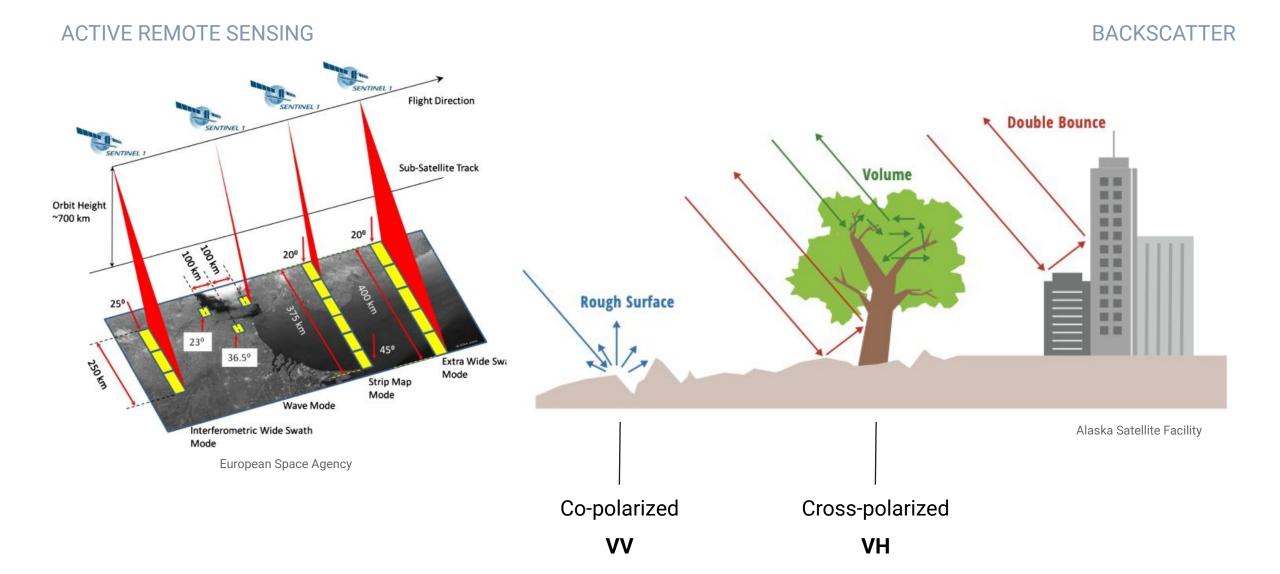
### **CLOUD COVER**



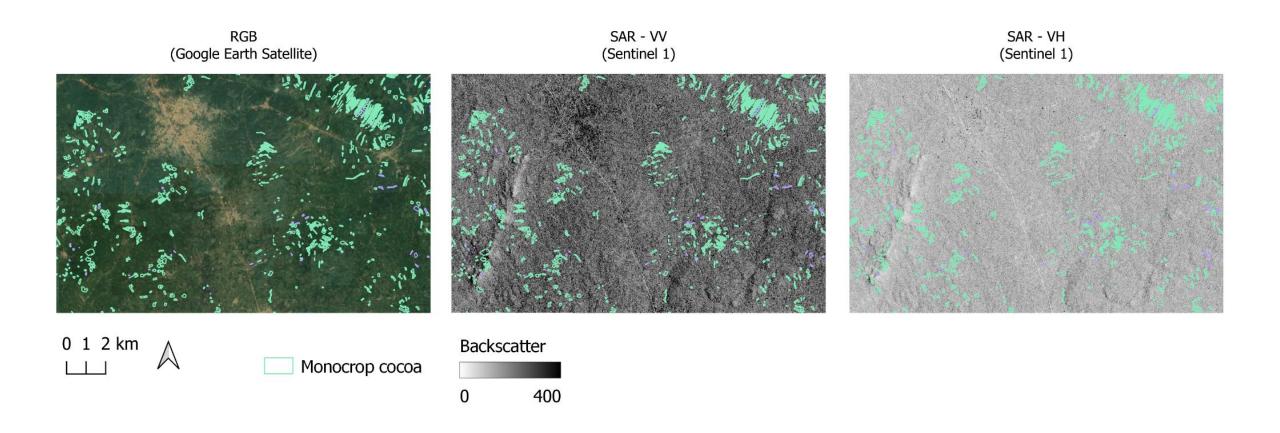




WEkEO, 2020

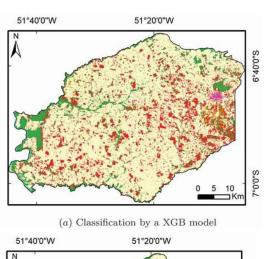


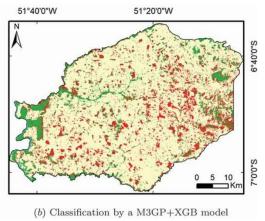
### **BACKSCATTER MAP**



# RELATED WORK

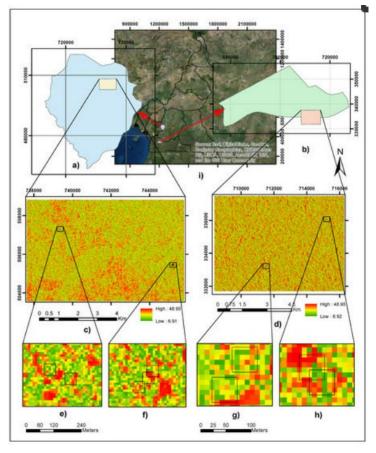
MSI



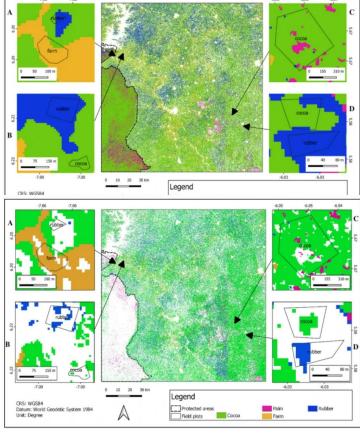


Batista et al., 2022

SAR



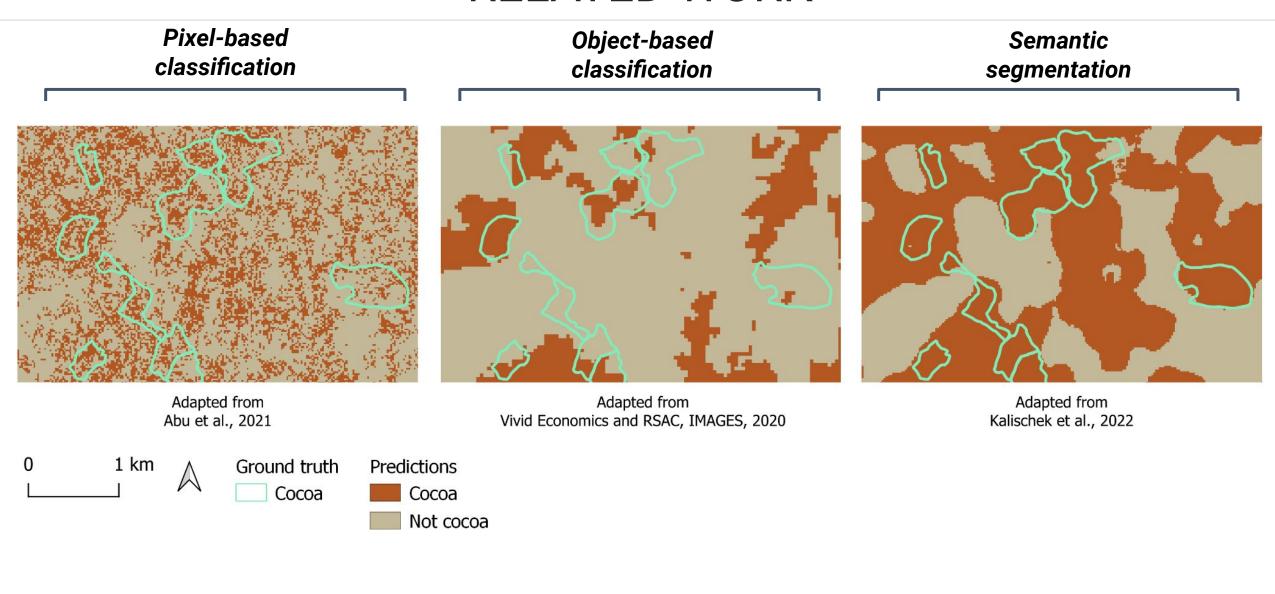
MSI + SAR



Numbisi & Van Coillie, 2020

Kanmegne Tamga et al., 2022

# RELATED WORK



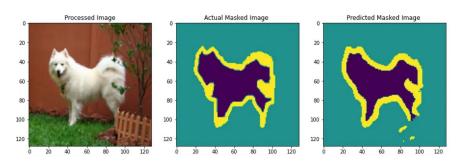
# **DEEP LEARNING**

### CONVOLUTIONAL NEURAL NETWORK

# Image Maps Input Output Convolutions Subsampling

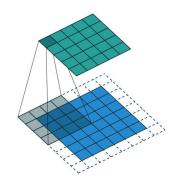
Fei-Kei et al., 2023

### SEMANTIC SEGMENTATION



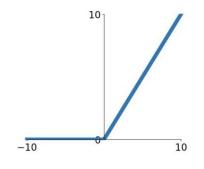
Bhatia, 2021

### **CONVOLUTIONAL LAYER**



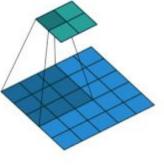
Dumoulin & Visin, 2016

### **ACTIVATION FUNCTION**



Fei-Kei et al., 2023

### **POOLING LAYER**



Dumoulin & Visin, 2016

# SEMANTIC SEGMENTATION

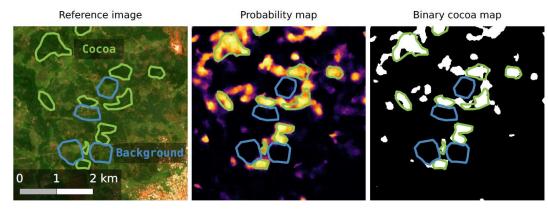
### **U-NET**

# RGB Ground Truth Predicted Background Background Cocoa Cocoa Uncertain

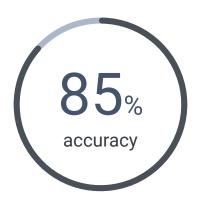
Adapted from Bonet Filella, 2018



### **XCEPTION**



Adapted from Kalischek et al., 2022

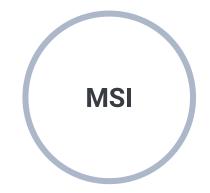


# SEMANTIC SEGMENTATION

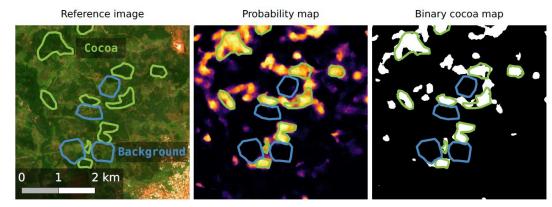
### **U-NET**

# RGB Ground Truth Predicted Background Background Cocoa Cocoa Uncertain

Adapted from Bonet Filella, 2018



### **XCEPTION**



Adapted from Kalischek et al., 2022



# RESEARCH QUESTIONS

To what extent can a Convolutional Neural Network (CNN) trained with multispectral imagery (MSI) **and** Synthetic Aperture Radar (SAR) datasets enable the automated detection of cocoa crops in Ghana?

- How does the combination of MSI and SAR data affect the results of cocoa parcel segmentation trained with data from a *single day*?
- How does the combination of MSI and SAR data affect the results of cocoa parcel segmentation trained with *temporal* datasets?
- Why does the use of different *polarizations* (i.e. Vertical-Vertical (VV) or Vertical-Horizontal (VH)) affect the influence of SAR datasets on the cocoa segmentation results?

4

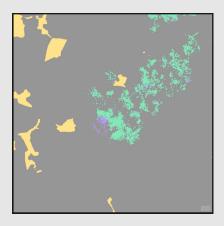
What is the impact of SAR and MSI training data on the detection of *intercrop* cocoa?

### **GROUND TRUTH POLYGONS**

Monocrop cocoa

Intercrop cocoa

Forest reserves





### SATELLITE DATA

MSI

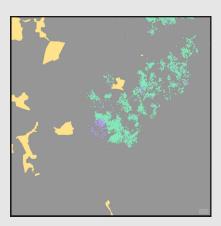
SAR

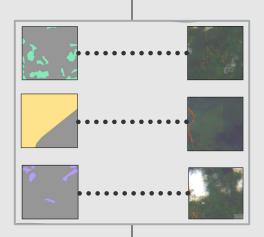


### **GROUND TRUTH POLYGONS**

Monocrop cocoa

Intercrop cocoa Forest reserves





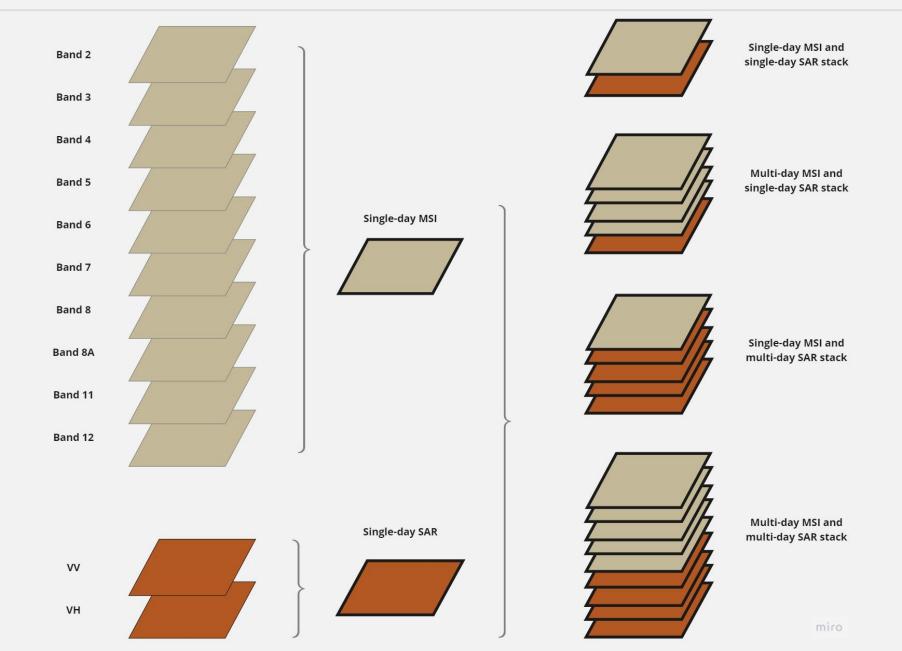
### SATELLITE DATA

MSI

SAR



# STACKING SATELLITE DATA



# TEMPORAL DATA

### SEASONS OF SOUTHERN GHANA



WET SEASON

# TEMPORAL DATA

### SEASONS OF SOUTHERN GHANA

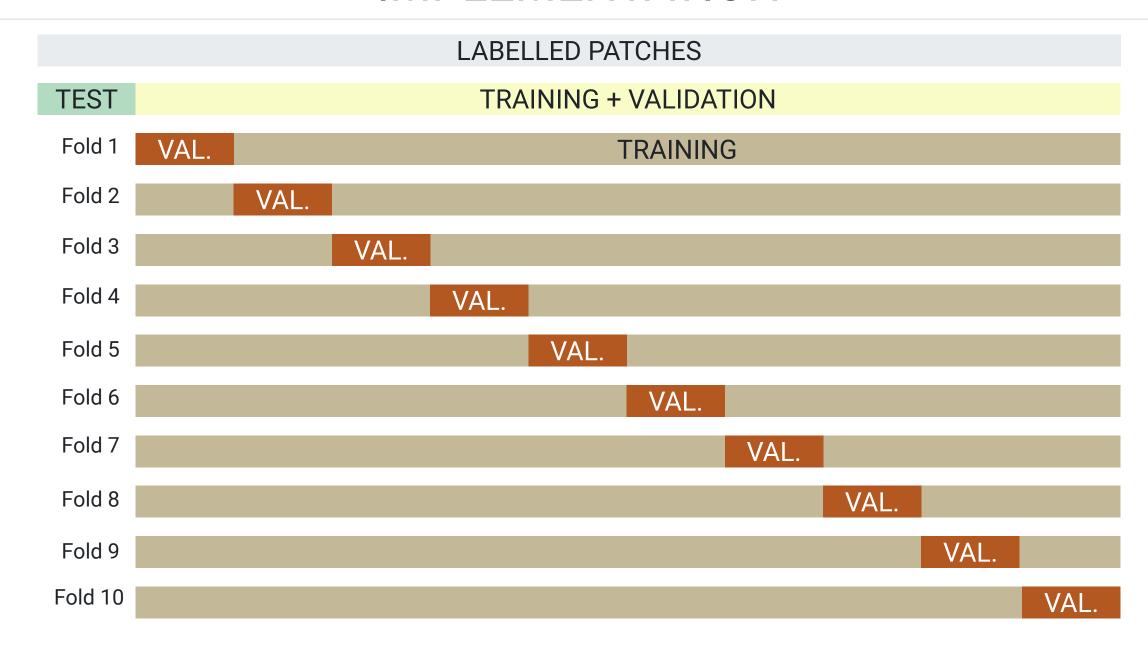
DRY SEASON

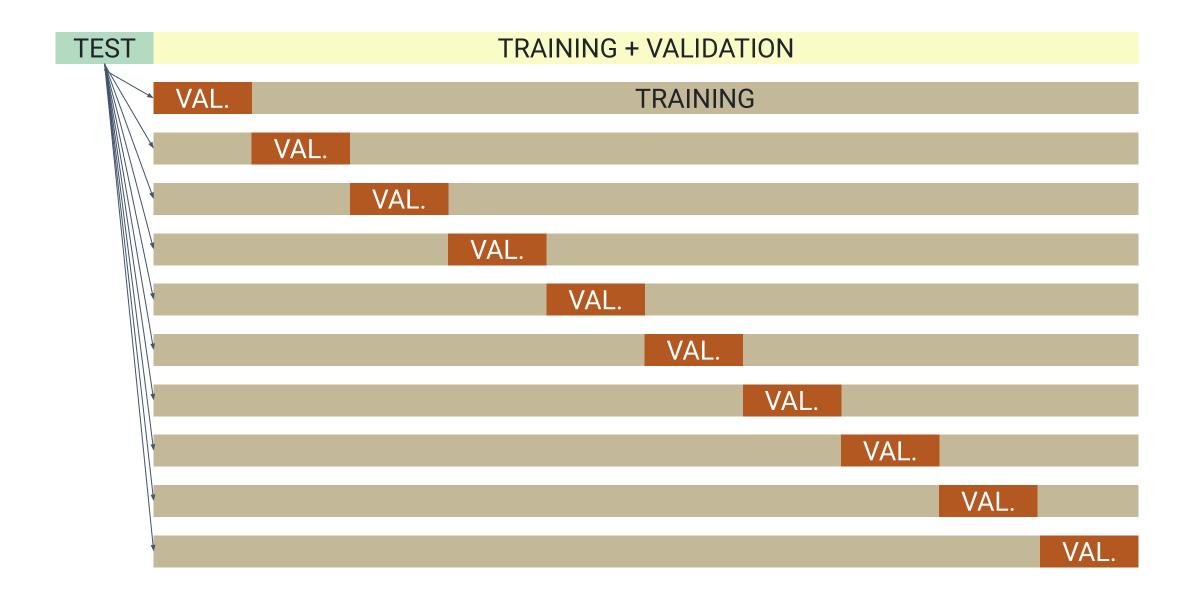


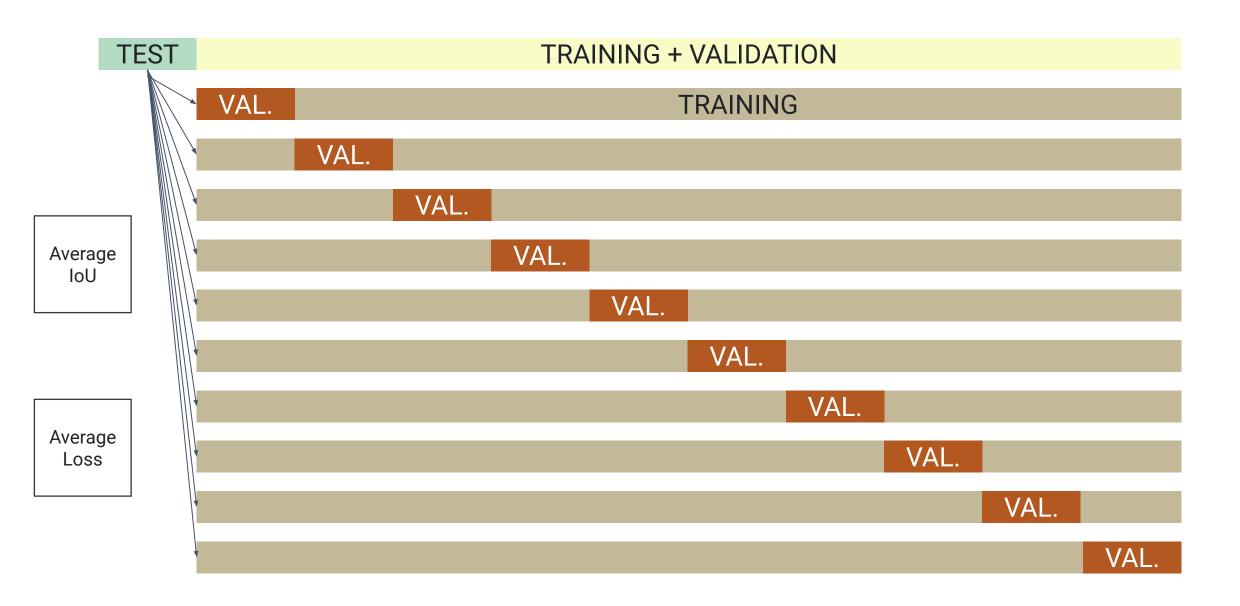
## TEMPORAL DATA

### SEASONS OF SOUTHERN GHANA

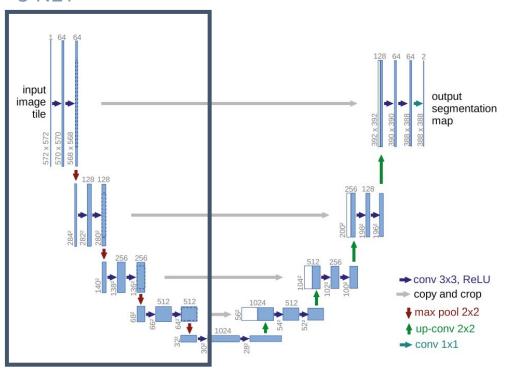






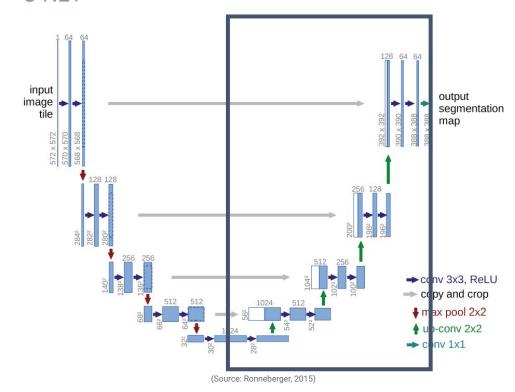


### **U-NET**

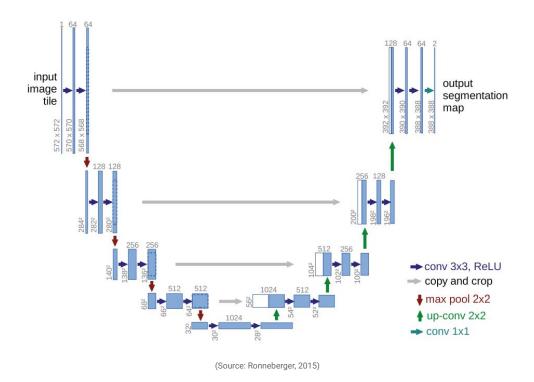


(Source: Ronneberger, 2015)

### **U-NET**



### **U-NET**



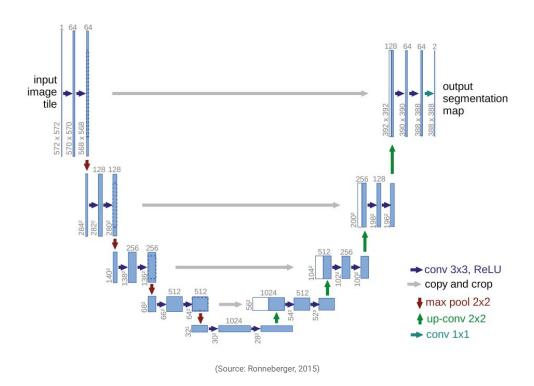
### WEIGHTED LOSS

$$w_c = \frac{1}{\frac{n_c}{N}}$$

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$$L_{cross-entropy}(\hat{y}, y) = -\frac{1}{N} \sum_{j}^{N} \sum_{c}^{M} w_c y_{c,j} \ln(\hat{y}_{c,j})$$

### **U-NET**



### WEIGHTED LOSS

$$w_c = \frac{1}{\frac{n_c}{N}}$$

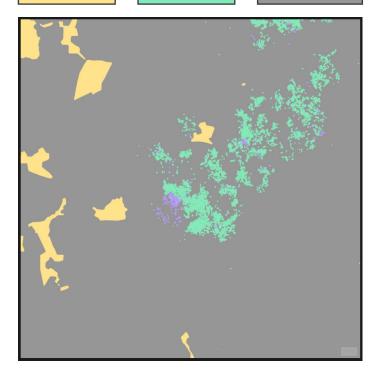
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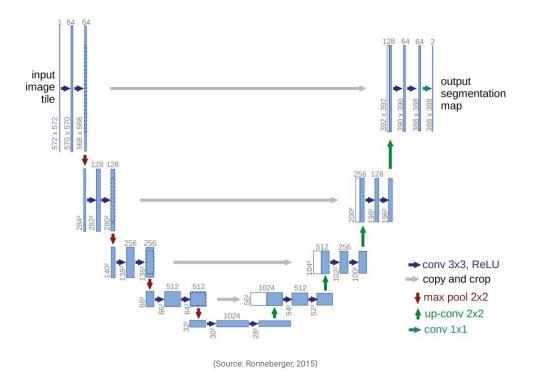




**Unknown** weight



### **U-NET**



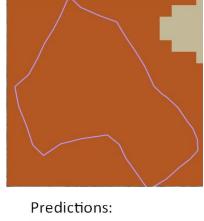
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$$L_{cross-entropy}(\hat{y}, y) = -\frac{1}{N} \sum_{j}^{N} \sum_{c}^{M} w_c y_{c,j} \ln(\hat{y}_{c,j})$$

### **Prediction map**

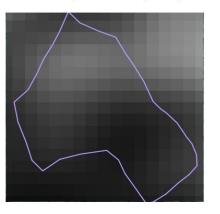


Cocoa

Forest

### OUTPUT

### Cocoa probability map

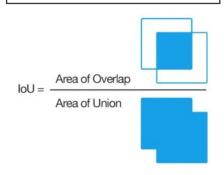


Cocoa probability



### **METRICS**

Intersection over Union (Cocoa class)



Loss value (All classes)



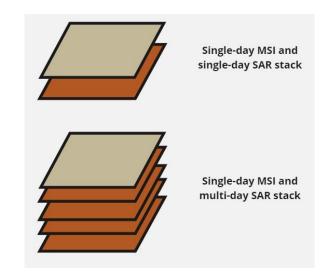
### **EXPERIMENTS**

Reference

Set	#	MSI Data	SAR Data	Season
1	1	December	N/A	Dry
	2	March	N/A	Dry
	3	Jan, March, December, Jan	N/A	Dry
	4	N/A	May - VV	Wet
	5	N/A	May - VH	Wet
	6	N/A	May - VV VH	Wet
	7	N/A	Jan - VV	Dry
	8	N/A	Jan - VH	Dry
	9	N/A	Jan - VV VH	Dry
	10	N/A	Jan, March, December, Jan - VV	Dry
	11	N/A	Jan, March, December, Jan - VH	Dry
	12	N/A	Jan, March, December, Jan - VV VH	Dry
	13	N/A	May, August, November, Jan - VV	Multi
	14	N/A	May, August, November, Jan - VH	Multi
	15	N/A	May, August, November, Jan - VV VH	Multi
	16	December	Jan - V V	Dry
	17	December	Jan - VH	Dry
	18	December	Jan - VV VH	Dry
	19	December	May - VV	Multi
	20	December	May - VH	Multi
	21	December	May - VV VH	Multi
	22	December	May, August, November, Jan - VV	Multi
	23	December	May, August, November, Jan - VH	Multi
	24	December	May, August, November, Jan - VV VH	Multi
	25	Jan, March, December, Jan	May - VV	Multi
	26	Jan, March, December, Jan	May - VH	Multi
	27	Jan, March, December, Jan	May - VV VH	Multi
	28	Jan, March, December, Jan	May, August, November, Jan - VV	Multi
2	29	December (label change)	N/A	Dry
	30	December	May	Multi
<u> </u>	31	December	May, August, November, Jan	Multi
3	32	December (cloudless)	N/A	Dry
	33	December	May	Multi
	34	December	May, August, November, Jan	Multi

### **EXPERIMENTS**

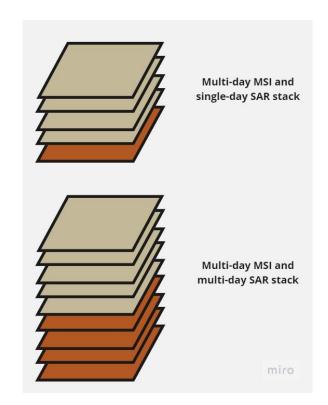
Set	#	MSI Data	SAR Data	Season
1	1	December	N/A	Dry
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	3	Jan, March, December, Jan	N/A	Dry
	4	N/A	May - VV	Wet
	5	N/A	May - VH	Wet
	6	N/A	May - VV VH	Wet
	7	N/A	Jan - VV	Dry
	8	N/A	Jan - VH	Dry
	9	N/A	Jan - VV VH	Dry
	10	N/A	Jan, March, December, Jan - VV	Dry
	11	N/A	Jan, March, December, Jan - VH	Dry
	12	N/A	Jan, March, December, Jan - VV VH	Dry
	13	N/A	May, August, November, Jan - VV	Multi
	14	N/A	May, August, November, Jan - VH	Multi
	15	N/A	May August November Jan - VV VH	Multi
	16	December	Jan - VV	Dry
	17	December	Jan - VH	Dry
	18	December	Jan - VV VH	Dry
	19	December	May - VV	Multi
	20	December	May - VH	Multi
	21	December	May - VV VH	Multi
	22	December	May, August, November, Jan - VV	Multi
	23	December	May, August, November, Jan - VH	Multi
	24	December	May, August, November, Jan - VV VH	Multi
	23	Jan, Marcn, December, Jan	Iviay - v v	Multi
	26	Jan, March, December, Jan	May - VH	Multi
	27	Jan, March, December, Jan	May - VV VH	Multi
	28	Jan, March, December, Jan	May, August, November, Jan - VV	Multi
2	29	December (label change)	N/A	Dry
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	33	December	May	Multi
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Single-day MSI

### **EXPERIMENTS**

Set	#	MSI Data	SAR Data	Season
1	1	December	N/A	Dry
	2	March	N/A	Dry
	3	Jan, March, December, Jan	N/A	Dry
	4	N/A	May - VV	Wet
	5	N/A	May - VH	Wet
	6	N/A	May - VV VH	Wet
	7	N/A	Jan - VV	Dry
	8	N/A	Jan - VH	Dry
	9	N/A	Jan - VV VH	Dry
	10	N/A	Jan, March, December, Jan - VV	Dry
	11	N/A	Jan, March, December, Jan - VH	Dry
	12	N/A	Jan, March, December, Jan - VV VH	Dry
	13	N/A	May, August, November, Jan - VV	Multi
	14	N/A	May, August, November, Jan - VH	Multi
	15	N/A	May, August, November, Jan - VV VH	Multi
	16	December	Jan - VV	Dry
	17	December	Jan - VH	Dry
	18	December	Jan - VV VH	Dry
	19	December	May - VV	Multi
	20	December	May - VH	Multi
	21	December	May - VV VH	Multi
	22	December	May, August, November, Jan - VV	Multi
	23	December	May, August, November, Jan - VH	Multi
	24	December	May, August, November, Jan - VV VH	Multi
	25	Jan, March, December, Jan	May - VV	Multi
	26	Jan, March, December, Jan	May - VH	Multi
	27	Jan, March, December, Jan	May - VV VH	Multi
	28	Jan, March, December, Jan	May, August, November, Jan - VV	Multi
	29	December (label change)	N/A	Dry
	30	December	May	Multi
	31	December	May, August, November, Jan	Multi
3	32	December (cloudless)	N/A	Dry
	33	December	May	Multi
	34	December	May, August, November, Jan	Multi

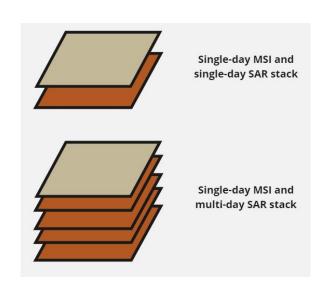


Multi-day MSI

### **EXPERIMENTS**

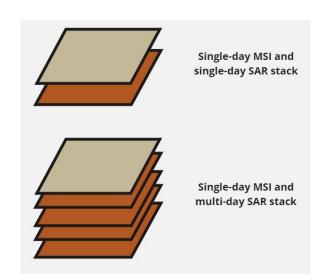
Set	#	MSI Data	SAR Data	Seasor
1	1	December	N/A	Dry
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	6	N/A	May - VV VH	Wet
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	8	N/A	Jan - VH	Dry
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	12	N/A	Jan, March, December, Jan - VV VH	Dry
	13	N/A	May, August, November, Jan - VV	Multi
	14	N/A	May, August, November, Jan - VH	Multi
	15	N/A	May, August, November, Jan - VV VH	Multi
	16	December	Jan - VV	Dry
	17	December	Jan - VH	Dry
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	20	December	May - VH	Multi
	21	December	May - VV VH	Multi
	22	December	May, August, November, Jan - VV	Multi
	23	December	May, August, November, Jan - VH	Multi
	24	December	May, August, November, Jan - VV VH	Multi
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	33	December	May	Multi
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Expanded "Not Cocoa" class

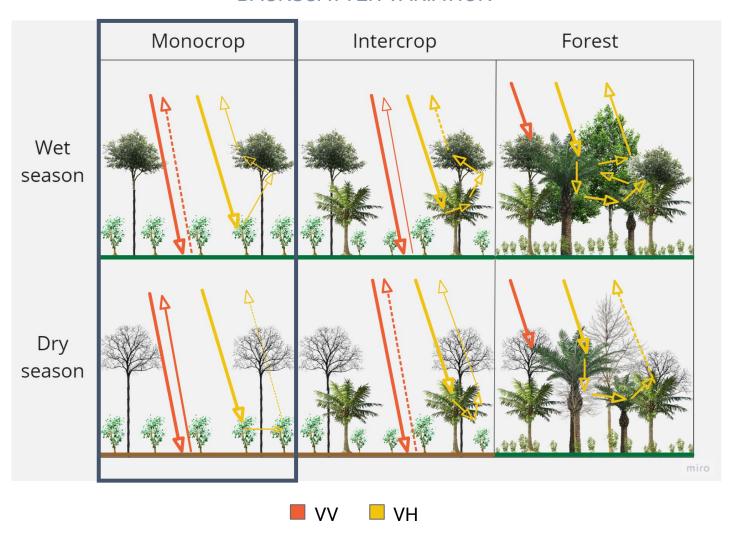


### **EXPERIMENTS**

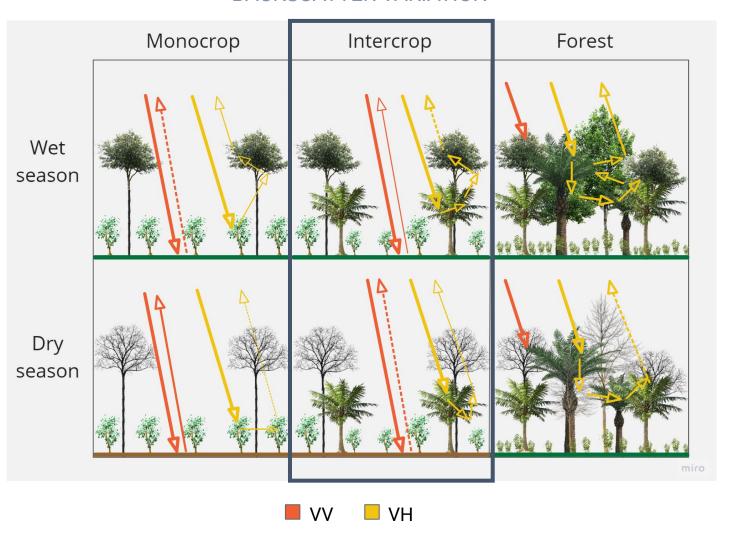
1		MSI Data	SAR Data	Season
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	3	Jan, March, December, Jan	N/A	Dry
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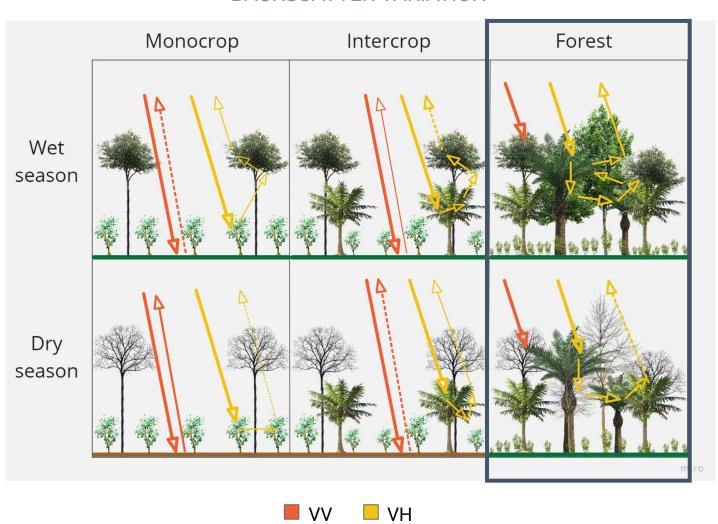
### **BACKSCATTER VARIATION**



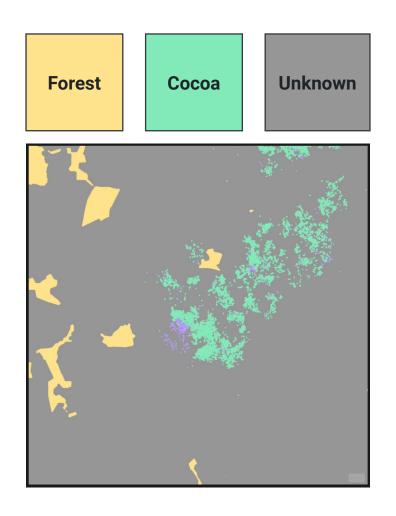
### **BACKSCATTER VARIATION**



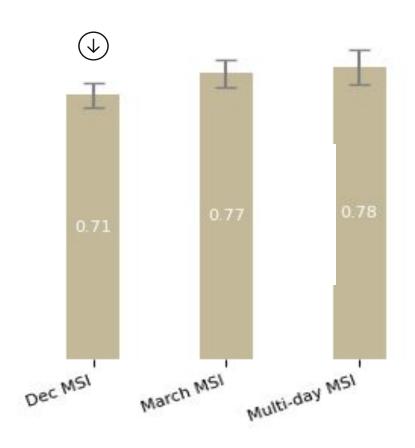
### **BACKSCATTER VARIATION**



# SET 1 RESULTS

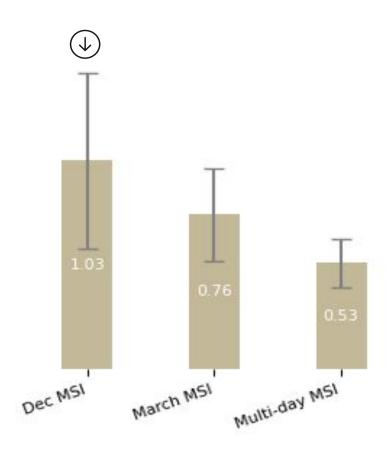


## **RESULTS - REFERENCE**



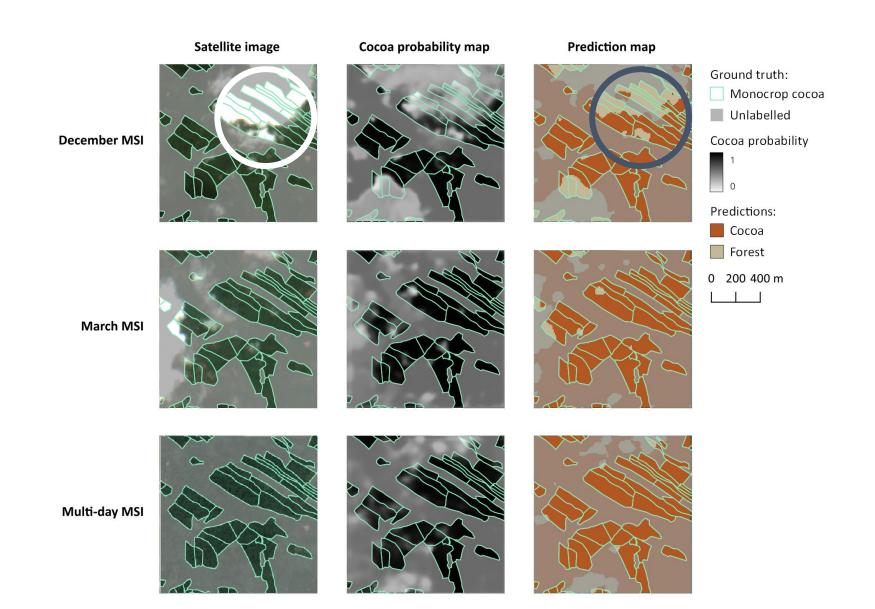
Intersection over Union

MSI only

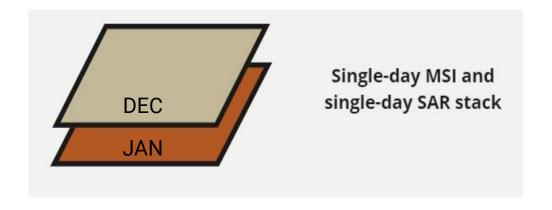


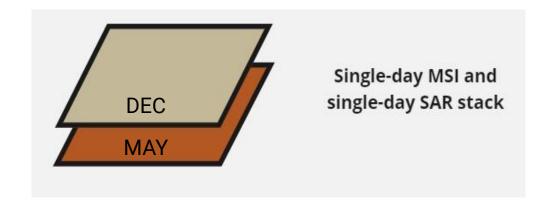
Loss MSI only

## **RESULTS - REFERENCE**

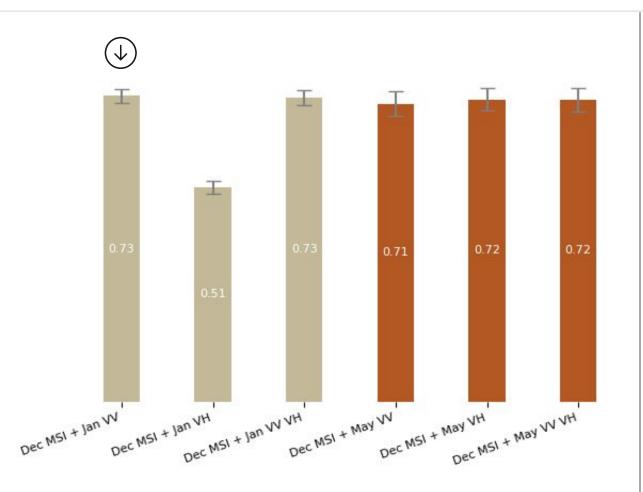


#### SINGLE DAY MSI + SINGLE DAY SAR



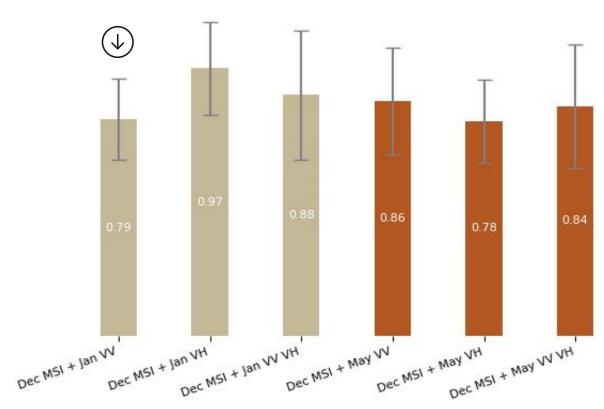


#### SINGLE DAY MSI + SINGLE DAY SAR



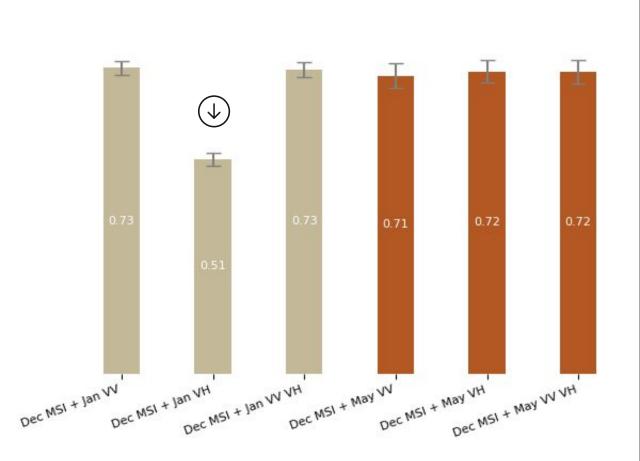
Intersection over Union

Single-day MSI + Single-day SAR



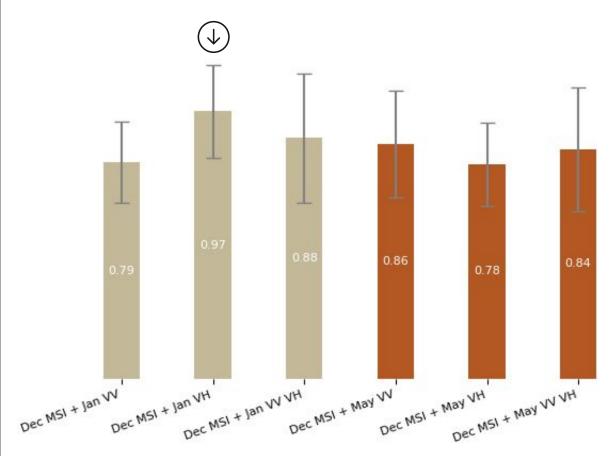
Loss
Single-day MSI + Single-day SAR

#### SINGLE DAY MSI + SINGLE DAY SAR



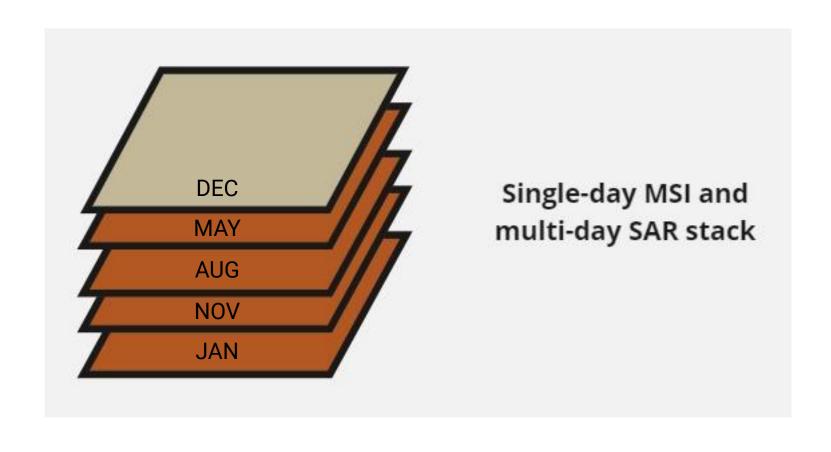
Intersection over Union

Single-day MSI + Single-day SAR

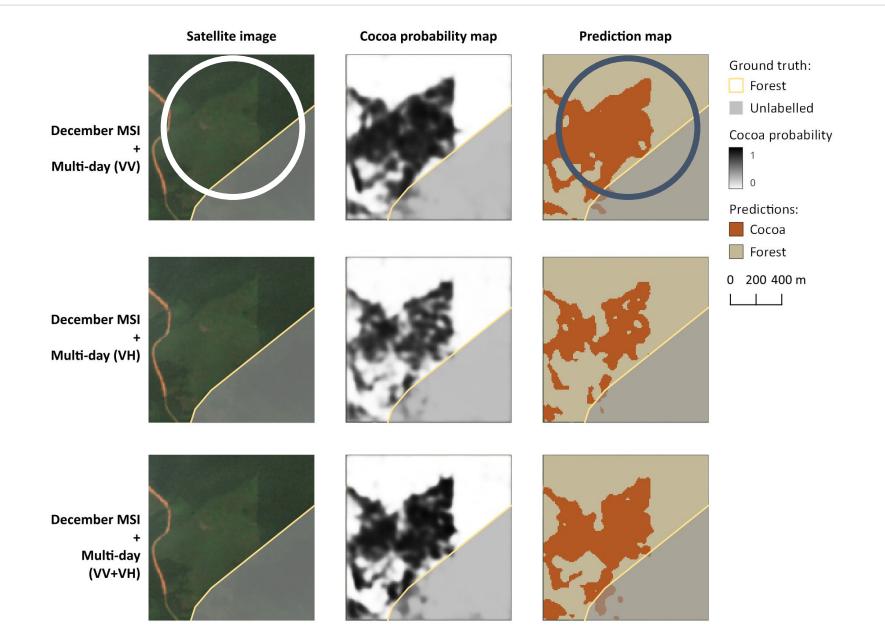


Loss
Single-day MSI + Single-day SAR

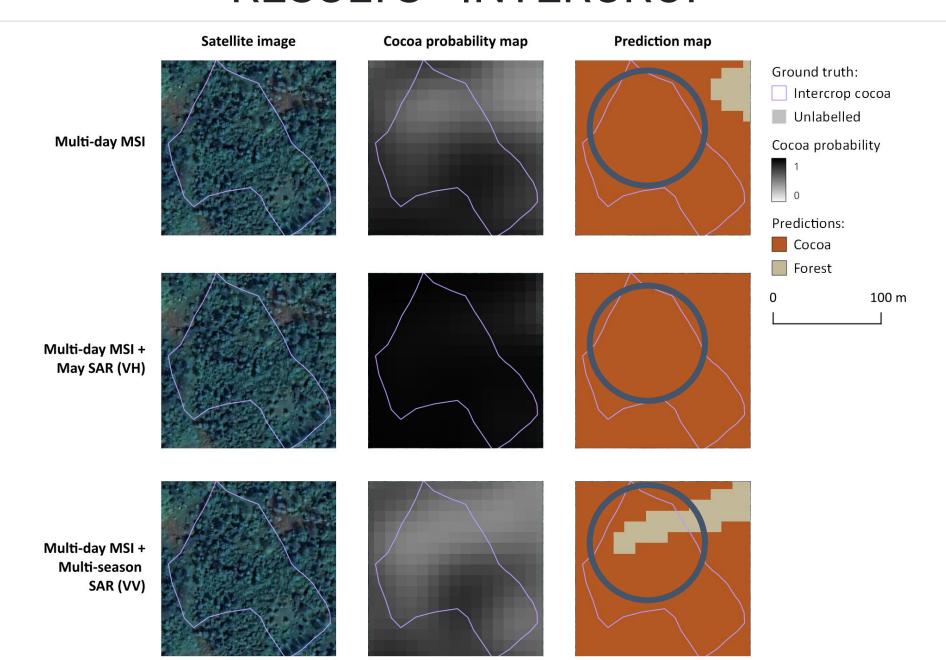
#### SINGLE DAY MSI + MULTI DAY SAR



### **RESULTS - SINGLE DAY MSI**



# **RESULTS - INTERCROP**



# **RESULTS - OTHER CROPS**

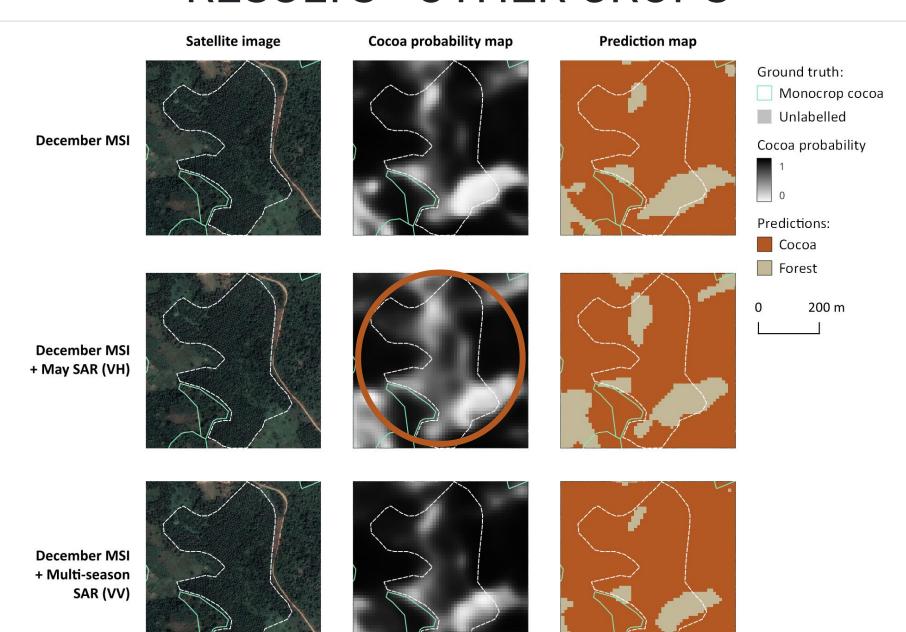


EOS Data Analytics

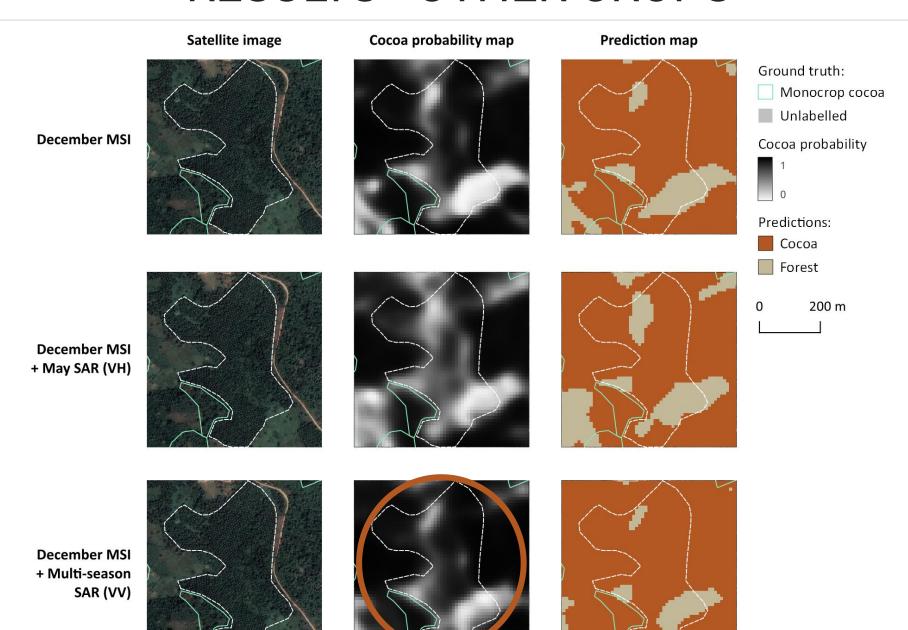


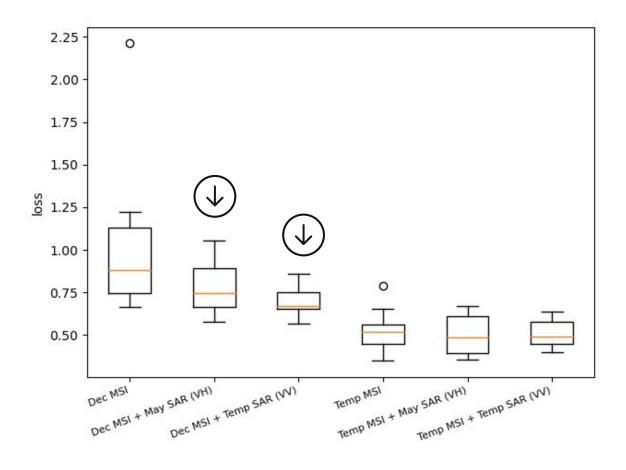
Google Earth Satellite

## **RESULTS - OTHER CROPS**



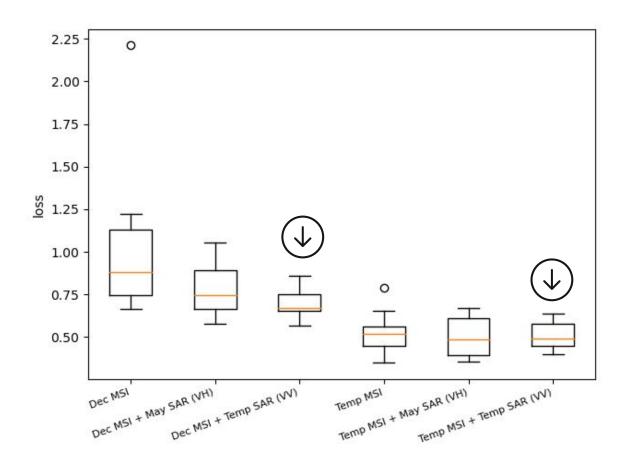
## **RESULTS - OTHER CROPS**





Loss

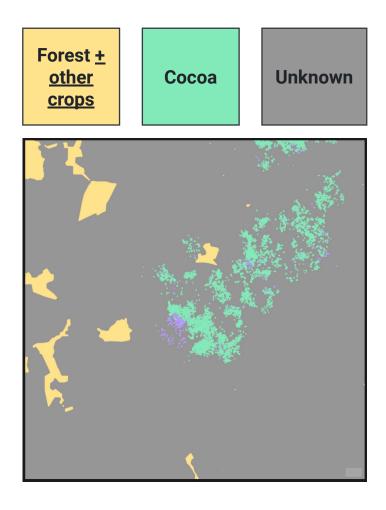
**MSI + SAR experiments** 

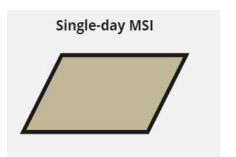


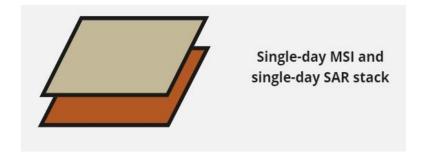
Loss

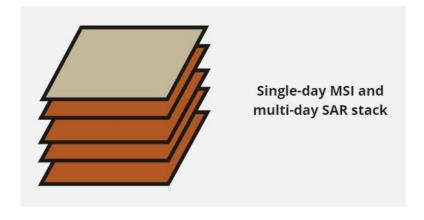
**MSI + SAR experiments** 

# SET 2 RESULTS

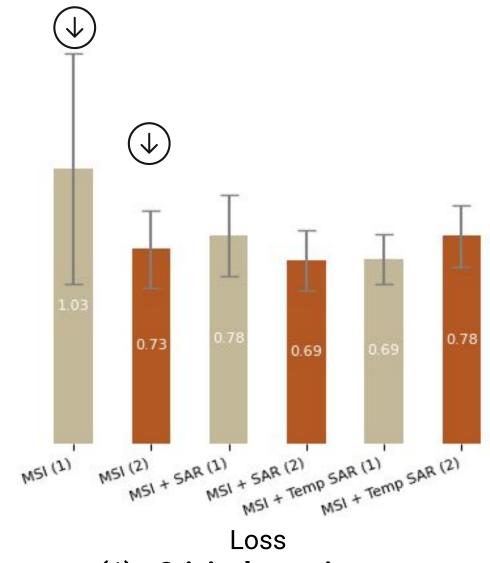








### RESULTS - SET 2

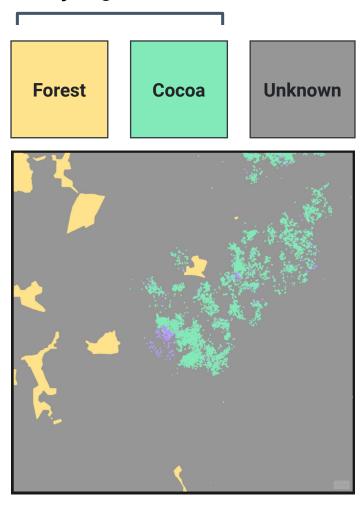


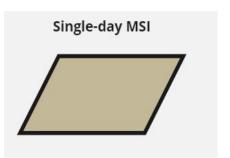
(1) Original experiments

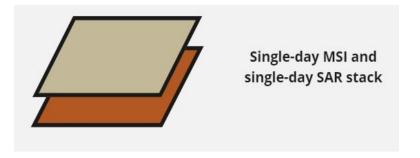
(2) Modified Labels

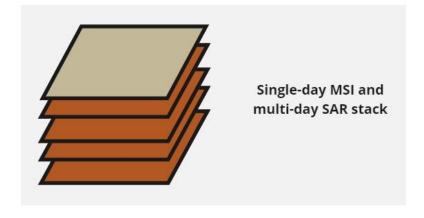
### SET 3 RESULTS

#### Cloudy regions removed

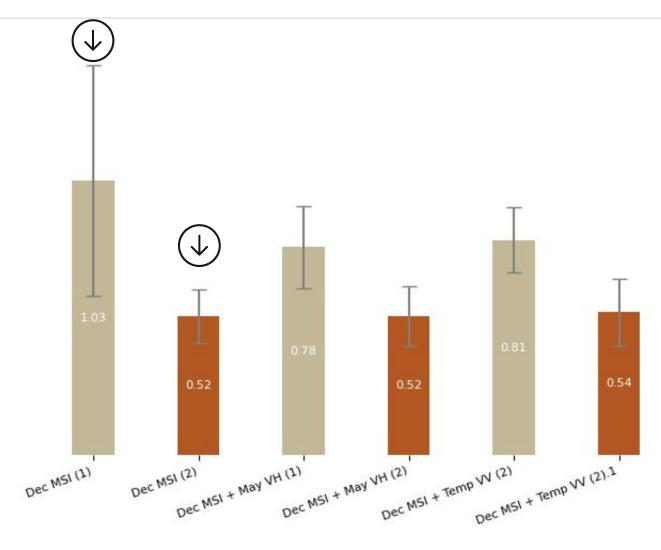






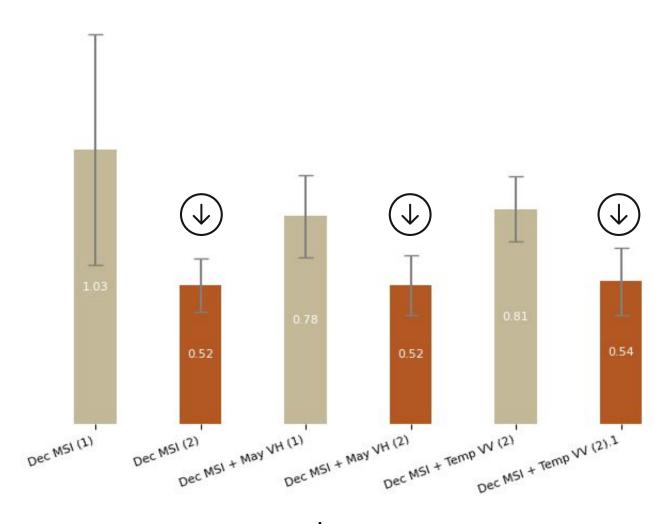


### **RESULTS - SET 3**



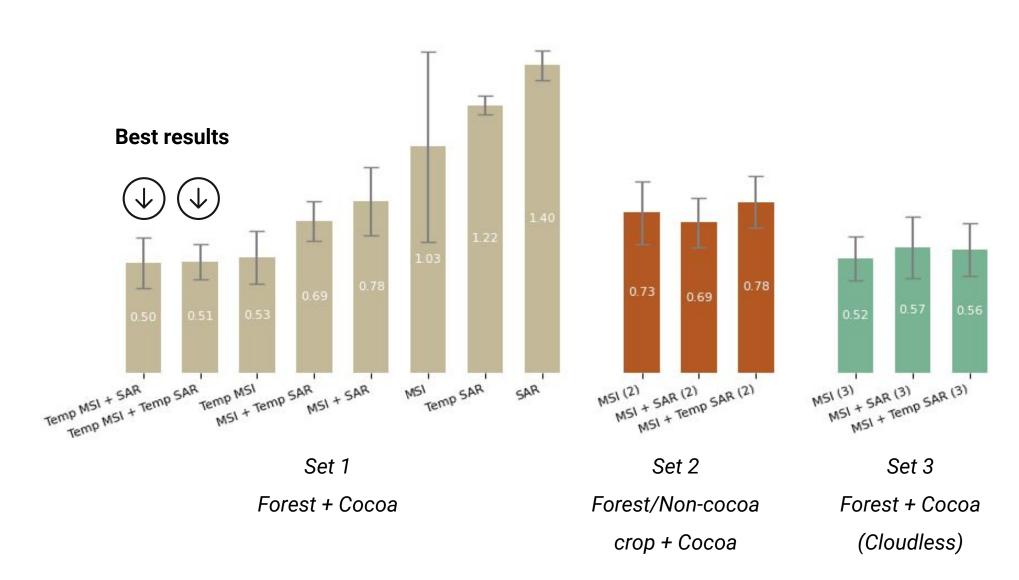
Loss
(1) Original experiments
(2) Clouds removed

### **RESULTS - SET 3**

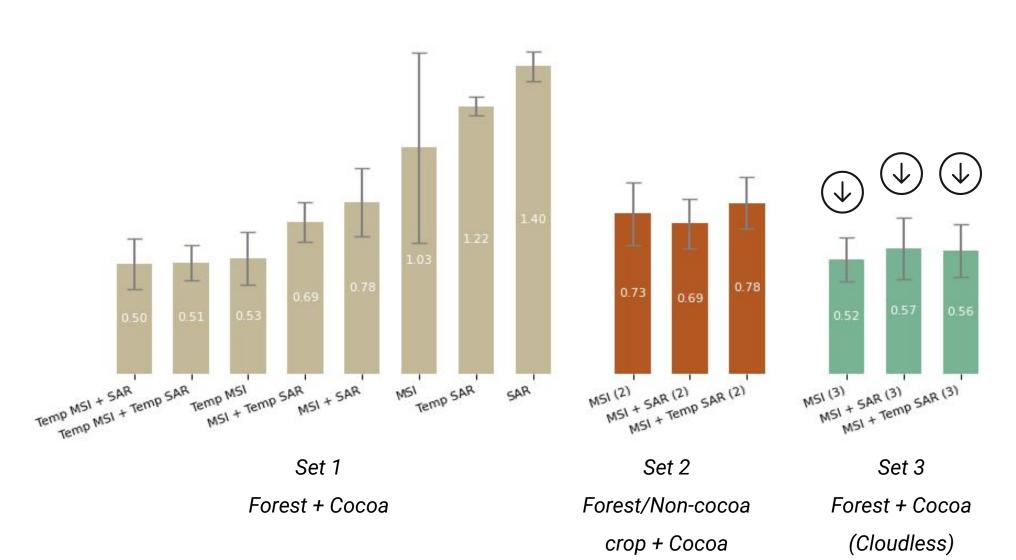


Loss
(1) Original experiments
(2) Clouds removed

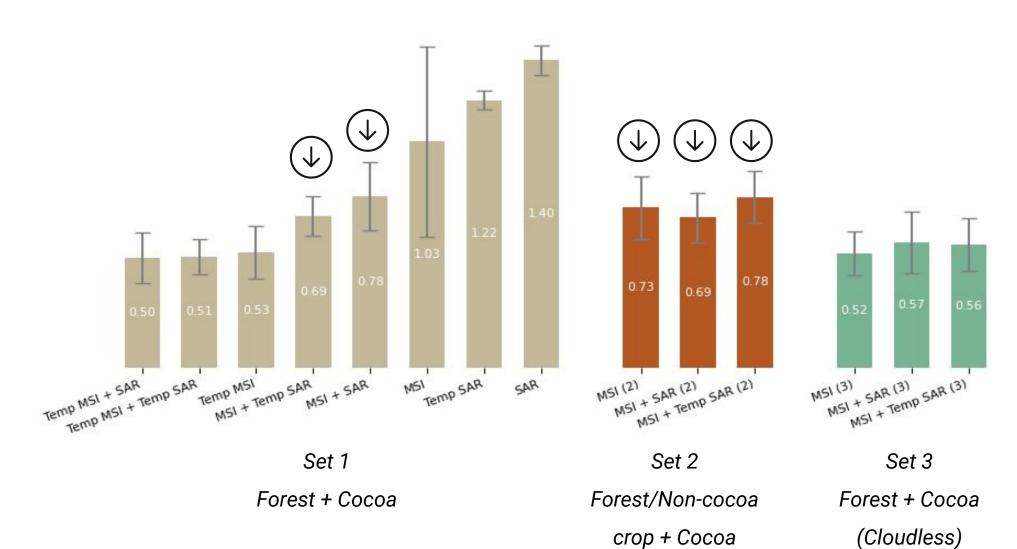
#### **Loss values**

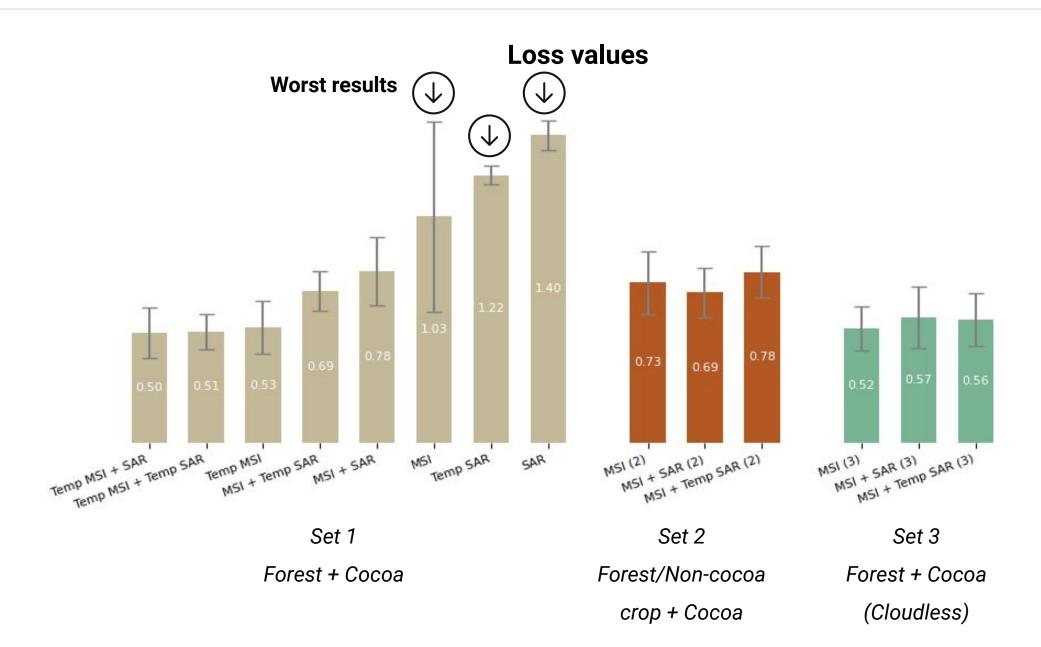


#### **Loss values**



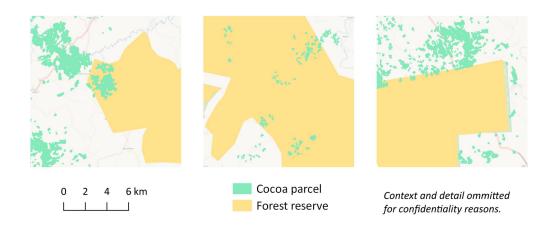
#### **Loss values**



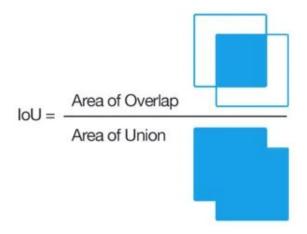


#### LIMITATIONS

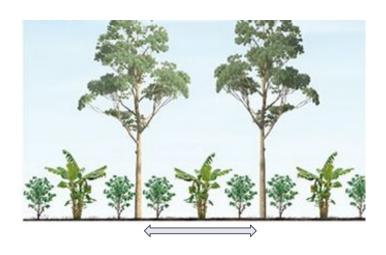
#### MISSING / UNCERTAIN GROUND TRUTH



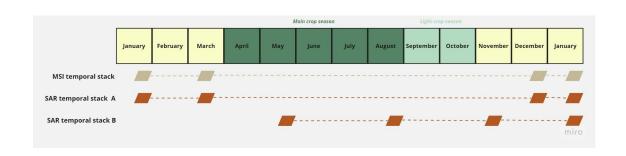
#### **METRICS**



#### LOW SPATIAL RESOLUTION



#### LOW TEMPORAL RESOLUTION



#### CONCLUSION

How does the combination of MSI and SAR data affect the results of cocoa parcel segmentation trained with data from a *single day*?

- + Single-day SAR
- ++ Multi-day SAR

How does the combination of MSI and SAR data affect the results of cocoa parcel segmentation trained with *temporal* datasets?

Not statistically significant

Possible improvement for non-vegetation land cover



#### CONCLUSION

- 3
- Why does the use of different *polarizations* (i.e. Vertical-Vertical (VV) or Vertical-Horizontal (VH)) affect the influence of SAR datasets on the cocoa segmentation results?
- + Complementary data (relevant season and polarization)
- Noisy data or similar backscatter

4

What is the impact of SAR and MSI training data on the detection of *intercrop* cocoa?

**Cannot draw quantitative conclusions** 

Possible increased sensitivity to vegetation types



#### CONCLUSION

To what extent can a Convolutional Neural Network (CNN) trained with multispectral imagery (MSI) **and** Synthetic Aperture Radar (SAR) datasets enable the automated detection of cocoa crops in Ghana?

- SAR data can be combined with MSI in order to train a U-NET for cocoa detection.

- The influence of SAR data is highly sensitive to seasonality, polarization and ground truth label classes.
- Satellite datasets must be chosen carefully based on the application and available ground truth data.



#### **FUTURE WORK**

#### **EXTEND CURRENT MODEL**

- Tuning U-NET hyperparameters
- Additional background land cover labels
- Higher temporal resolution satellite datasets
- Addition of height data
- Spectral / backscatter analysis

#### MODEL MODIFICATIONS

- Loss function (e.g. Lovasz, Dice)
- Architecture (e.g. Xception)



#### FEATURE EXTRACTION

- Vegetation indices (e.g. NDVI)
- Texture metrics (e.g. GLCM)
- Cross Ratio (VH/VV)

#### HIGHER PRECISION

- Longer SAR wavelengths (e.g. L, P-band)
- Higher resolution MSI
- Hyperspectral imagery

# Thank you!



TUDelft MERIDIA