

Reconocimiento de cultivos agrícolas en regiones tropicales usando secuencias de imágenes de teledetección de sensores activos y pasivos

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Outline

1. Introducción

2. CRFs

3. Resultados

4. Conclusiones

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1. Introducción

2. CRFs

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4. Conclusiones

Introducción

- Agricultura
 - Fuente de **sustento**
 - Contribuye a los **ingresos nacionales**
 - Fuente de **materia prima**
 - Suministro de **alimentos y pasto**

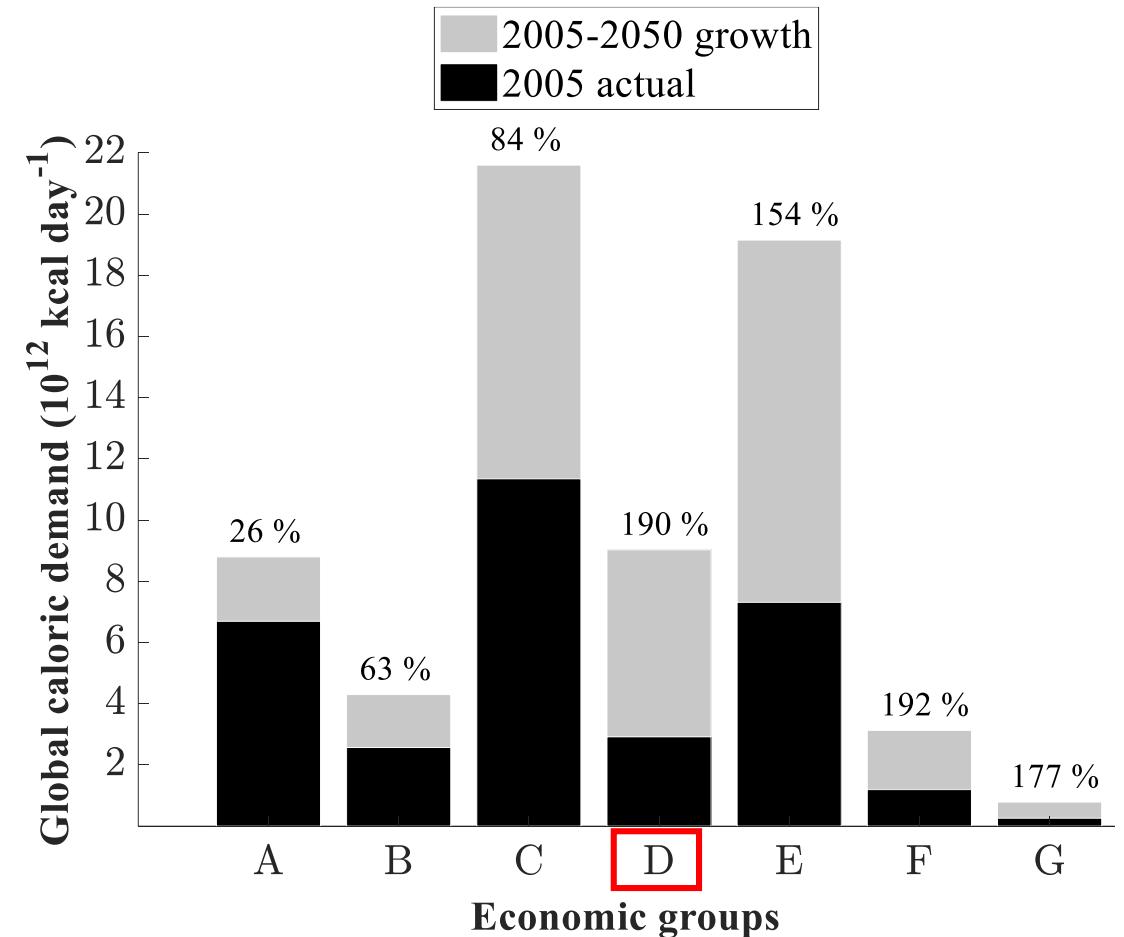


Introducción

- Agricultura – Retos
 - Reducir **impacto ambiental**

Introducción

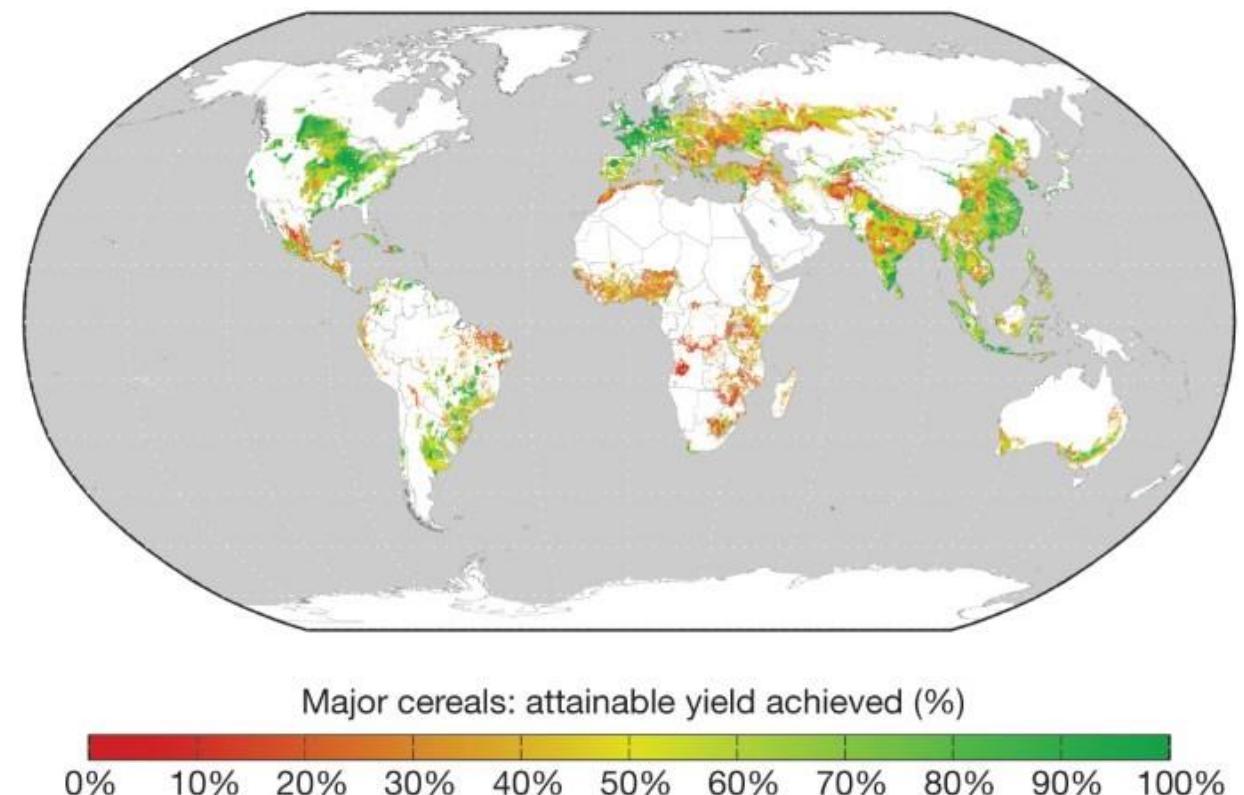
- Agricultura – Retos
 - Reducir **impacto ambiental**
 - Aumento de la **demanda de alimentos**



Fuente: FAO – UN (Food and Agriculture Organization of the United Nations)
THENKABAIL, P. S.. *Land resources monitoring, modeling, and mapping with remote sensing*. CRC Press, 2015.

Introducción

- Agricultura – Retos
 - Reducir **impacto ambiental**
 - Aumento de la **demandas de alimentos**
 - Reducir la brecha de rendimiento (*yield gap*)



Fuente: MUELLER, N. D.; GERBER, J. S.; JOHNSTON, M.; RAY, D. K.; RAMANKUTTY, N. ; FOLEY, J. A.. *Closing yield gaps through nutrient and water management*. Nature, 490(7419):254, 2012.

Introducción

- Agricultura – Soluciones
 - Mapear **tipos de cultivos y área cultivada**
 - Inventarios sobre cultivos
 - Predicción de rendimiento
 - Monitoreo de actividades agrícolas

Introducción

- Agricultura – Teledetección (*Remote Sensing*)

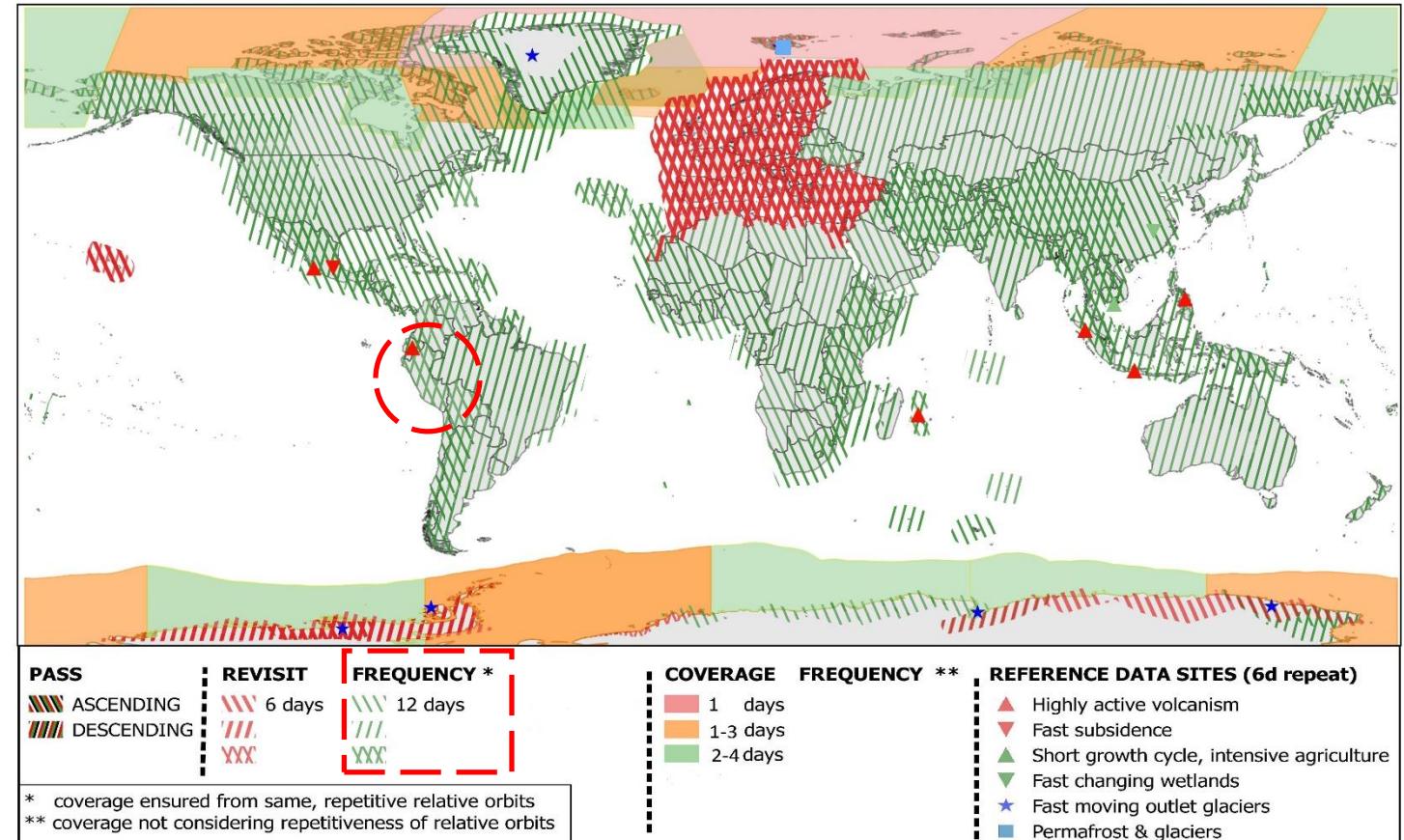
- Gran **cobertura**
- Alta **frecuencia y repetitivo**
- Costo **relativamente bajo**
- Resoluciones espaciales
 - Bajo, medio y alto

Source: European Space Agency – ESA
(<https://sentinel.esa.int/web/sentinel/missions/sentinel-1/observation-scenario>)

Sentinel-1 Constellation Observation Scenario: Revisit & Coverage Frequency



validity start: 02/2018



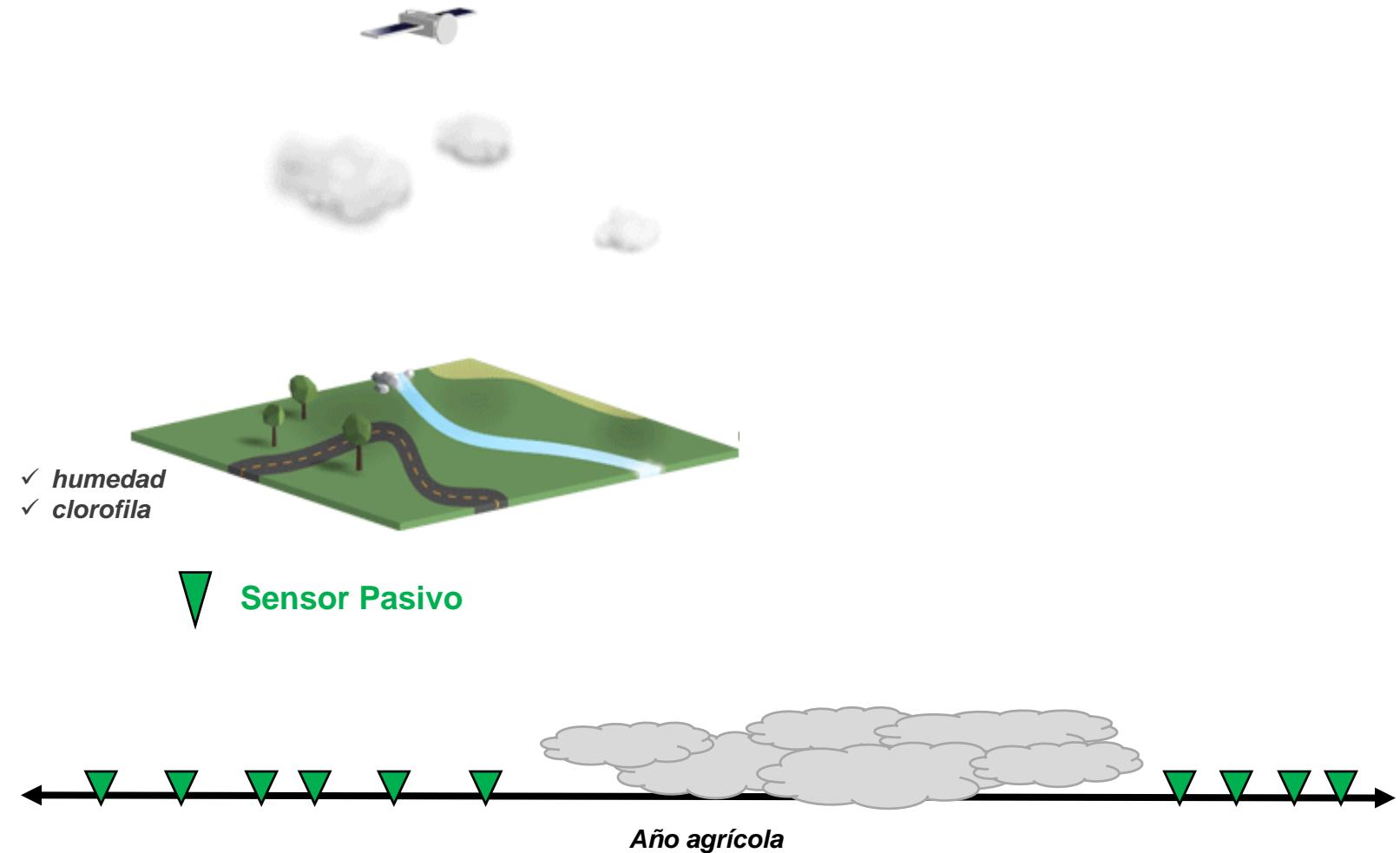
Introducción

- Teledetección (*Remote Sensing*)

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- Teledetección (*Remote Sensing*)
 - Sensores pasivos
 - Ópticos

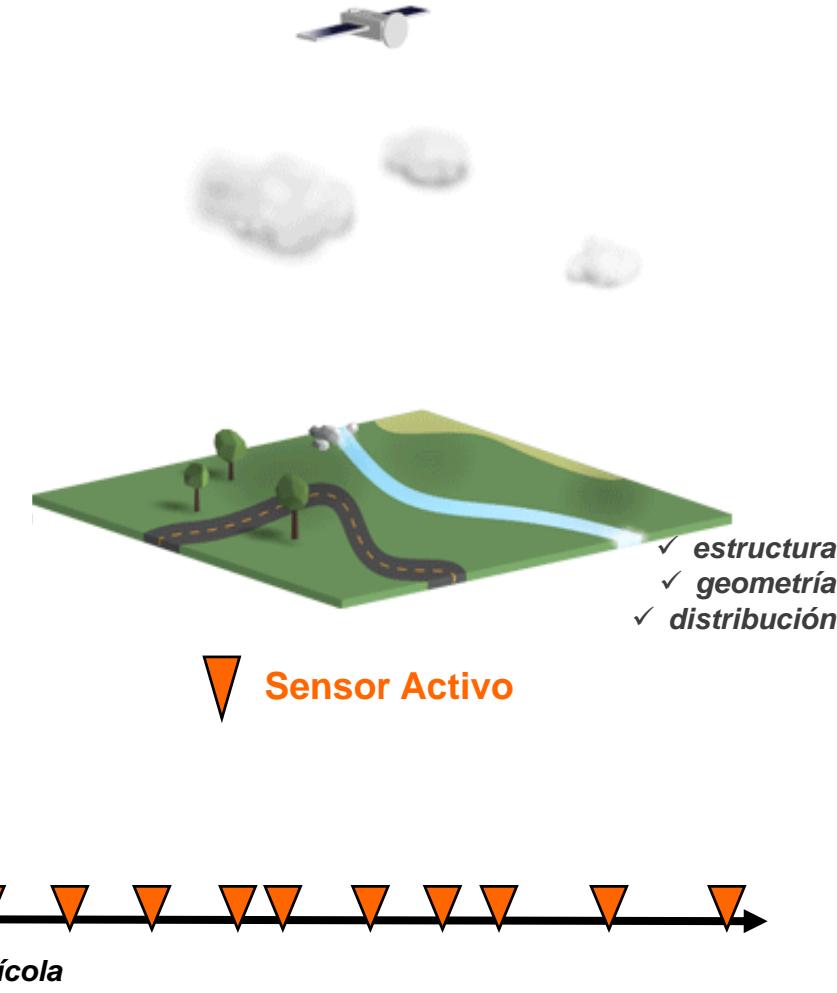
Source: NASA Earth Observatory (<https://earthobservatory.nasa.gov/features/SoilMoisture>)



Introducción

- Teledetección (*Remote Sensing*)

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- Sensores activos
 - Radar de apertura Sintética (SAR)



Introducción

- Teledetección (*Remote Sensing*)

- Sensores pasivos

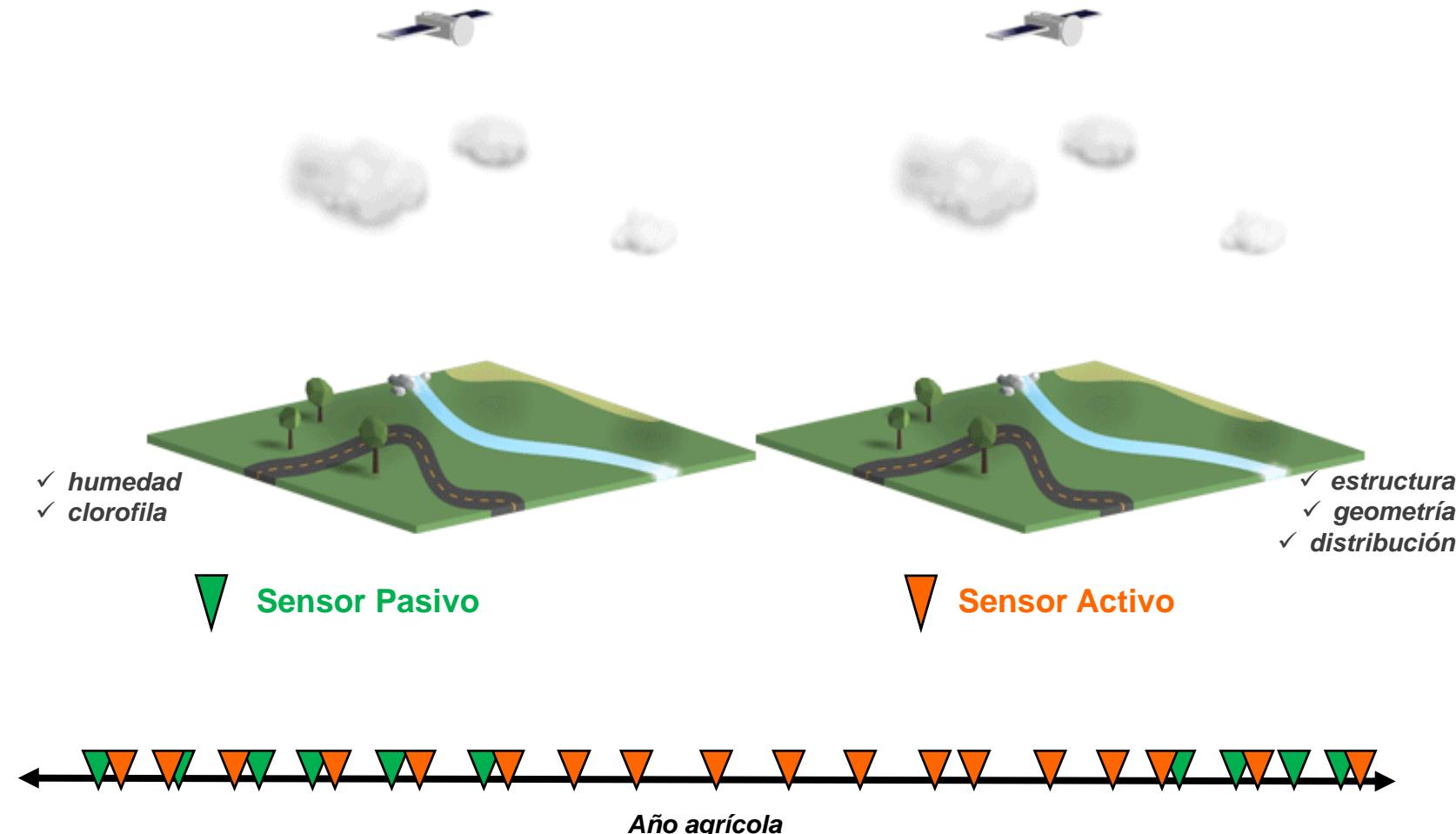
- Ópticos

- Sensores activos

- Radar de apertura

- Sintética (SAR)

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Introducción

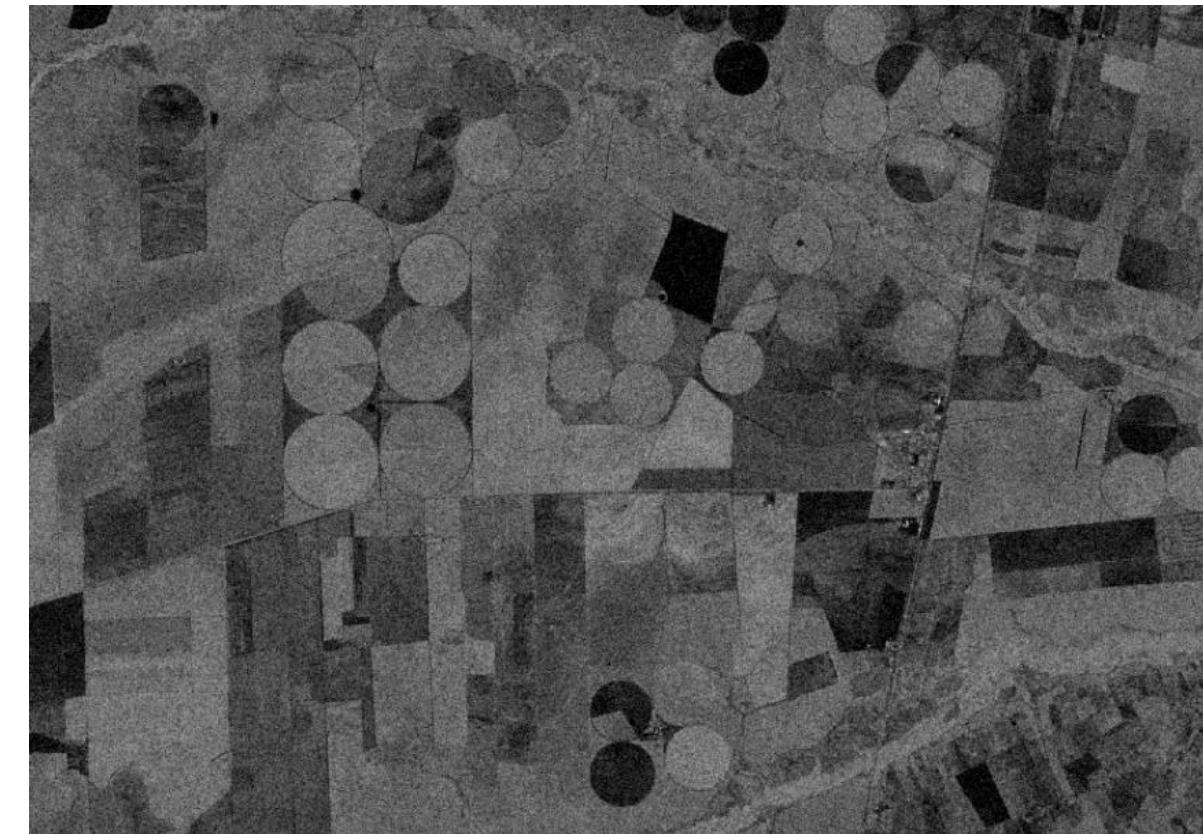
- Teledetección (*Remote Sensing*)

Composición RGB de imagen Sentinel-2A
adquirida el 19 de Junio, 2018 en Bahia, Brazil



Sensor Pasivo

Banda C, SAR, polarización VH, imagen Sentinel-1A
adquirida el 19 de Junio, 2018 en Bahia, Brazil



Sensor Activo

Introducción

- Características de Cultivos Agrícolas

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 - Información de contexto
 - “*everything is related to everything else, but near things are more related than distant things*” – Waldo Tobler.
(1st Law of Geography)

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 - Contexto Espacial



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- Contexto Espacial



- Contexto Temporal



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2. CRFs

3. Resultados

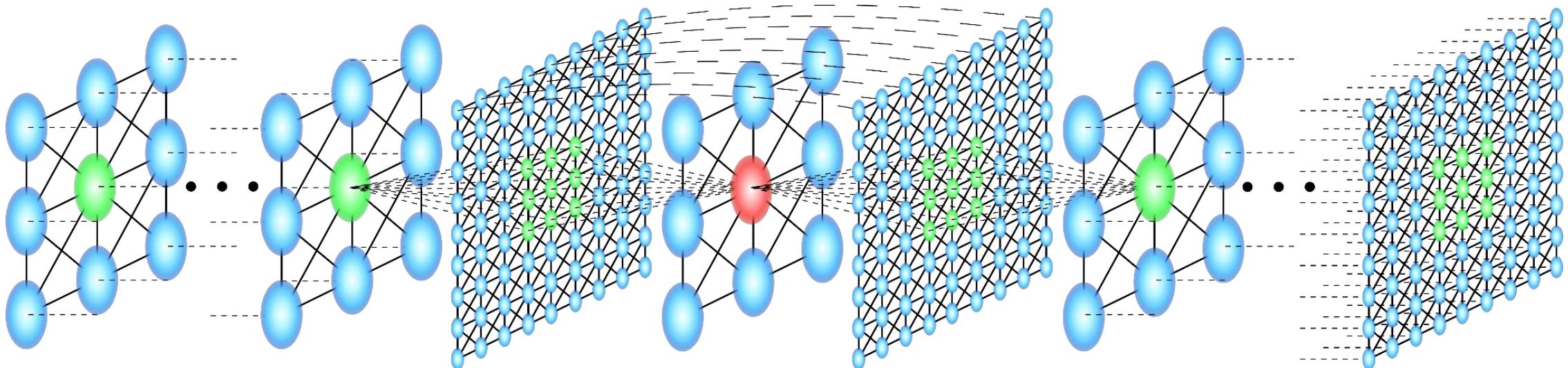
4. Conclusiones

Multi-temporal CRF

- Conditional Random Fields (CRFs)
- Clasificador discriminativo, basado en grafos

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Constante de Normalización

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Potencial de Asociación: relación entre datos y labels

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Potencial de Asociación: relación entre datos y labels

Potencial de Interacción Espacial: como un pixel interactúa con sus vecinos espaciales

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Potencial de Interacción Temporal: como un pixel interactúa con sus vecinos en el dominio temporal

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Pesos de cada potencial

Constante de Normalización

Potencial de Asociación: relación entre datos y labels

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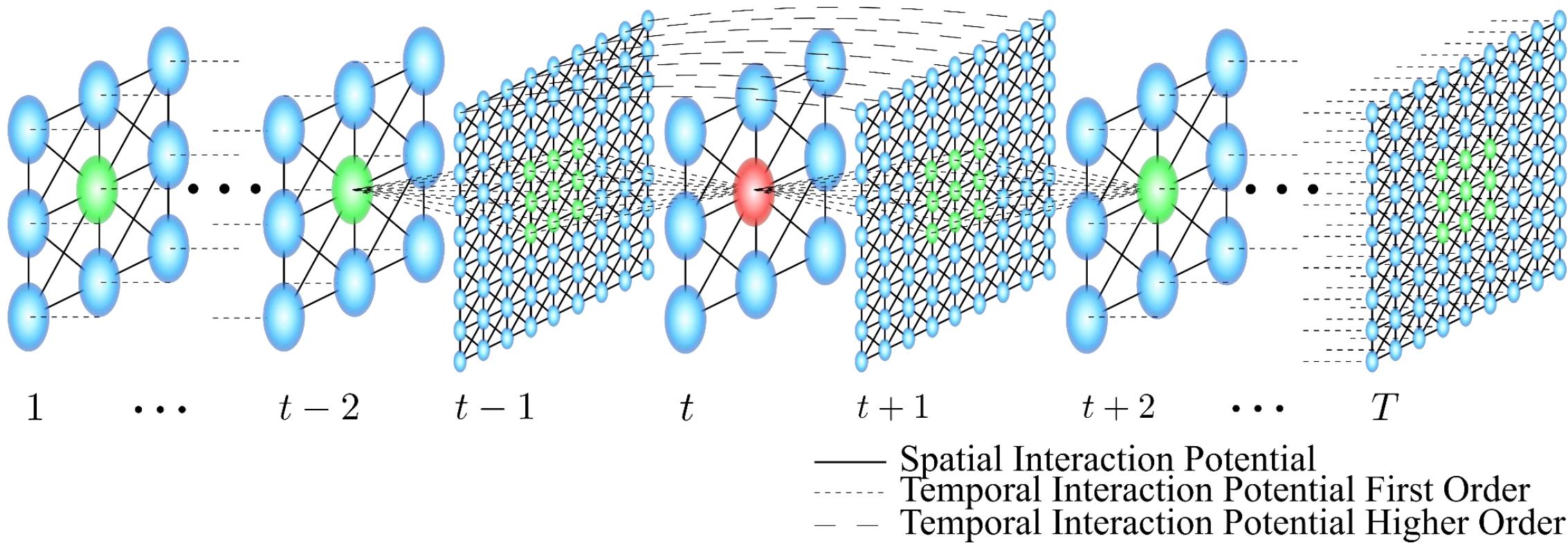
Potencial de Interacción Temporal: como un pixel interactúa con sus vecinos en el dominio temporal

Multi-temporal CRF

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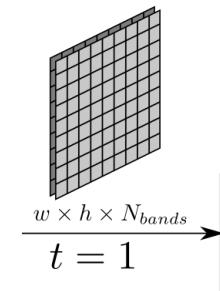
- **Potencial de Asociación**
 - Random Forest + atributos de textura (GLCM)
 - CNN usando cada imagen
 - CNN usando el stack de todas las imágenes
- **Potencial de Interacción Espacial**
 - Modelo Contrast-sensitive Potts
- **Potencial de Interacción Temporal**
 - Información de especialistas sobre transiciones posibles

Potencial de Asociación

Random Forest + atributos de textura (GLCM)

$$AP^t(y_{i,t}, \mathbf{x}) = \log P_{RF^t}(y_{i,t} | \mathbf{f}_{GLCM}(\mathbf{x}_{N_{i,t}}))$$

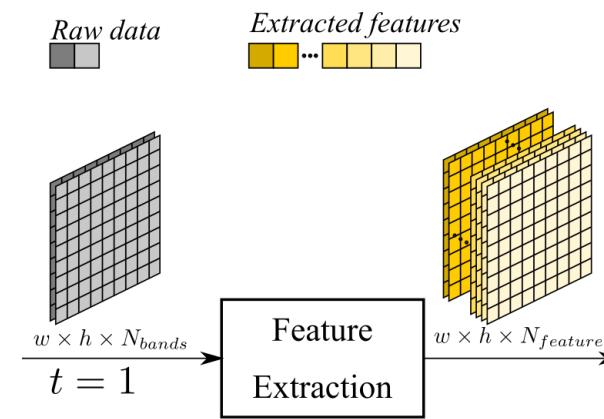
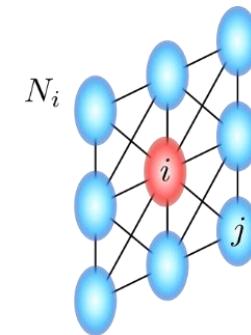
Raw data

Potencial de Asociación

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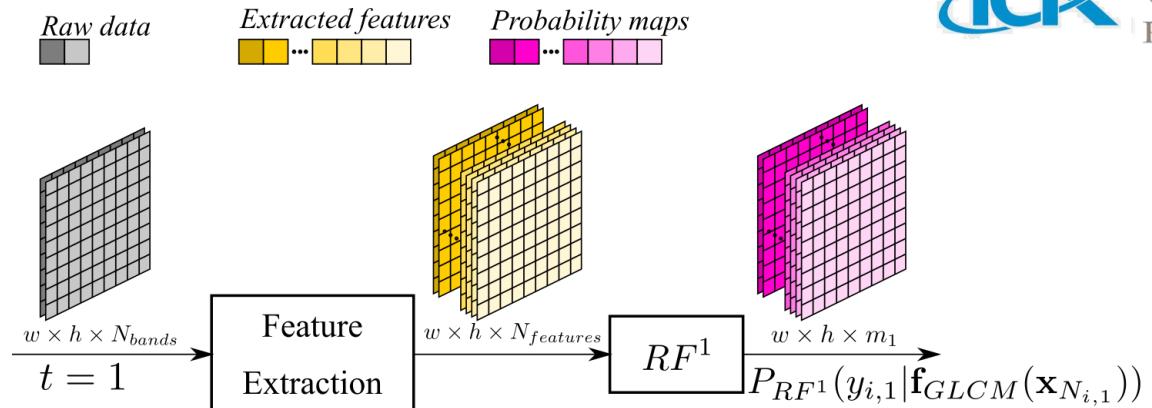
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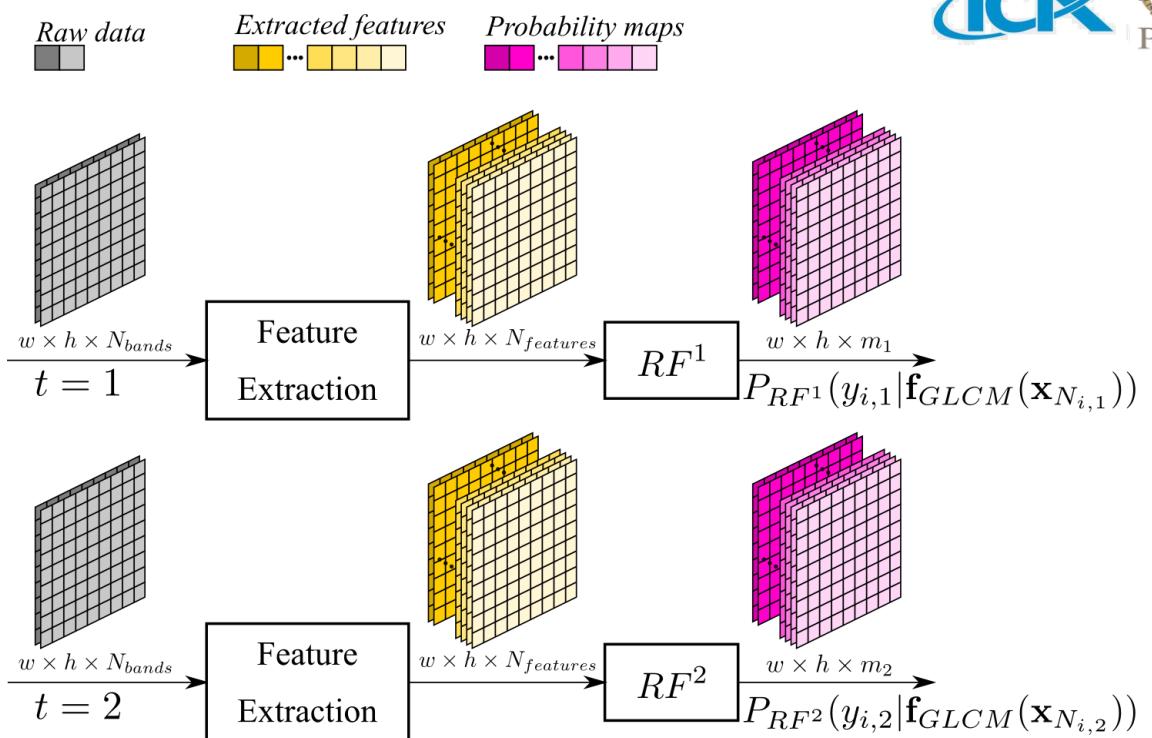
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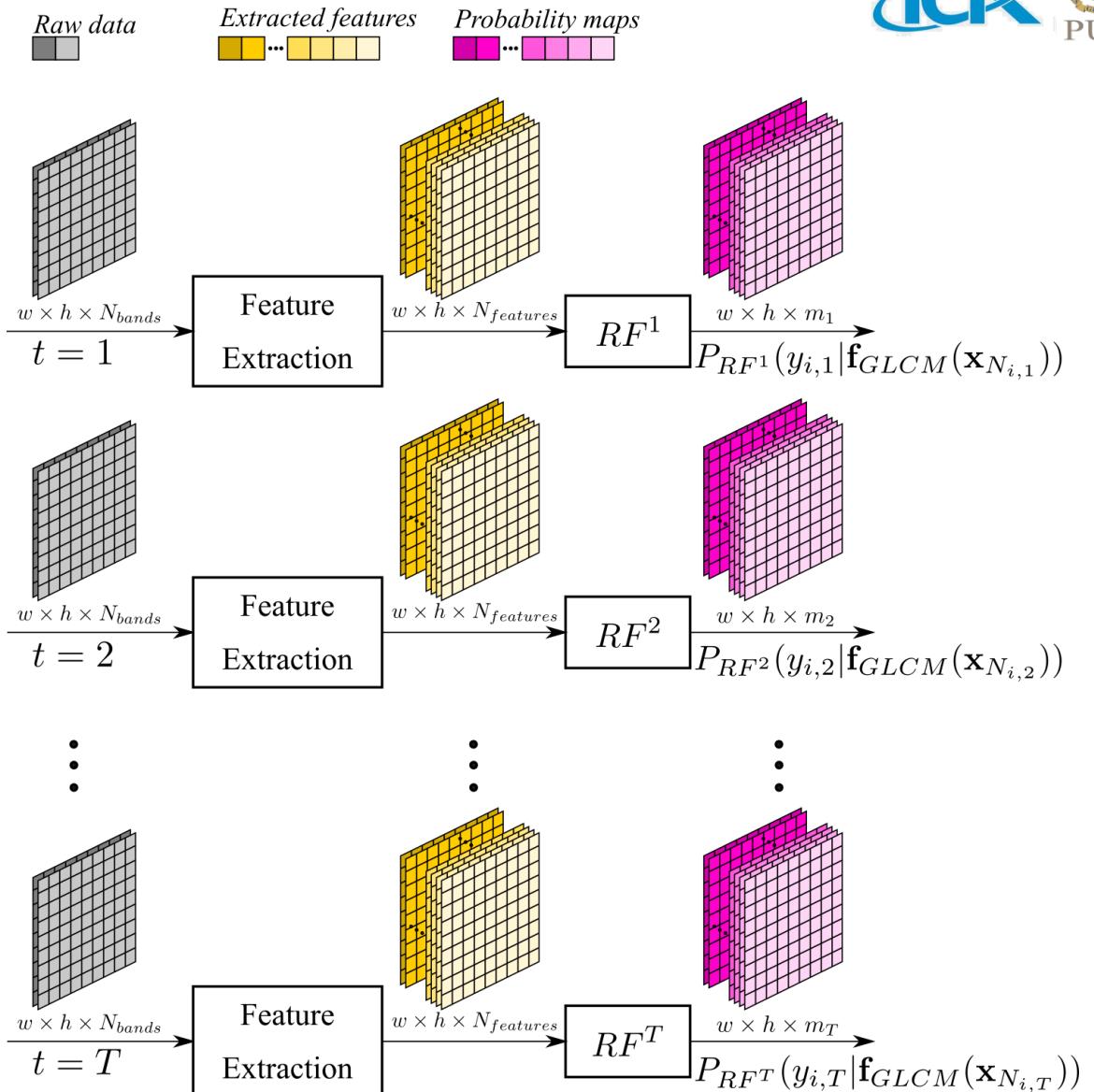
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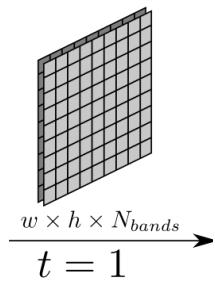


Potencial de Asociación

CNN usando cada imagen

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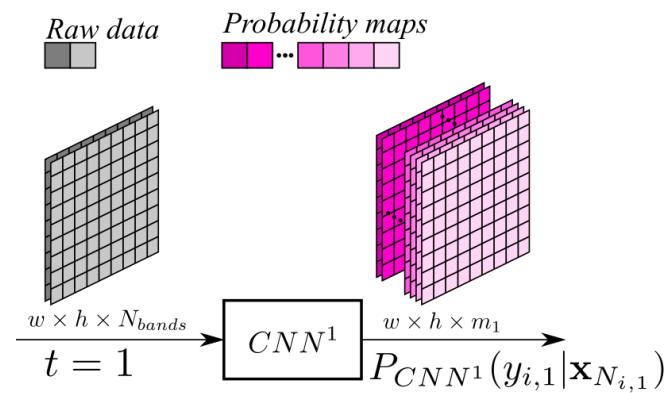
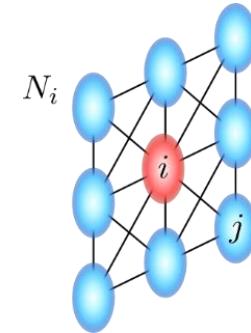
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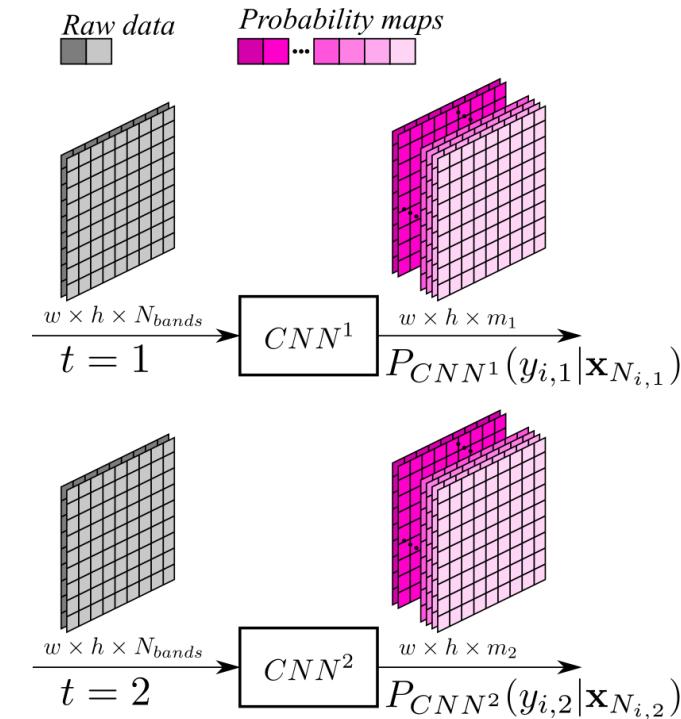
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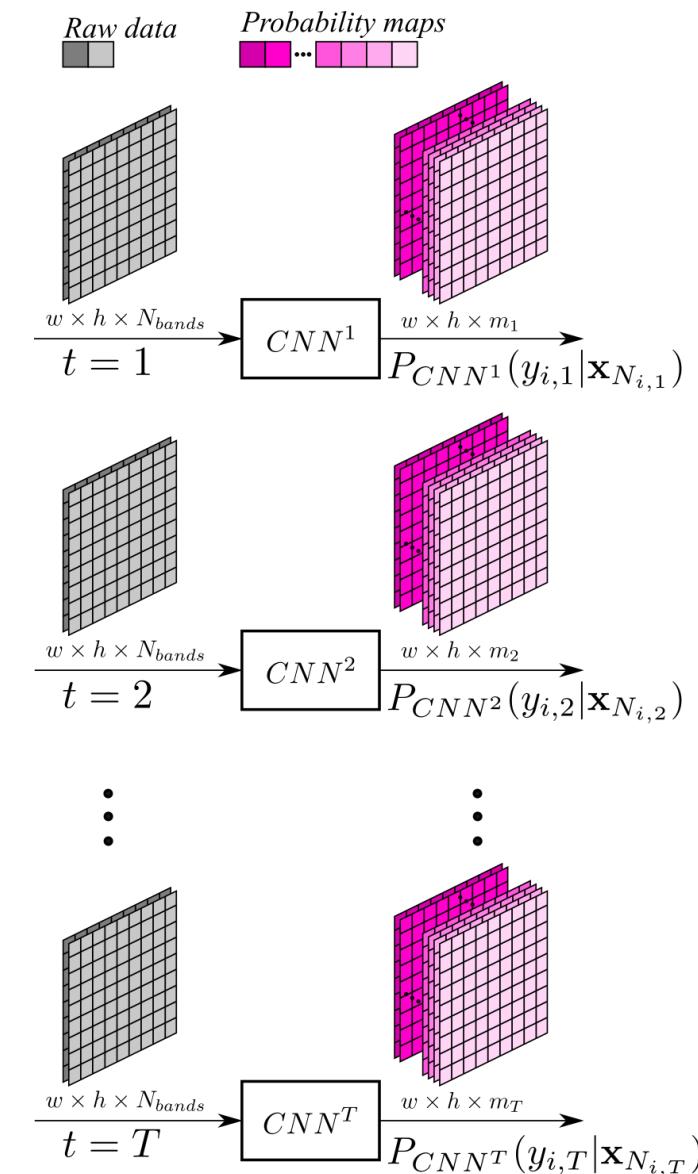
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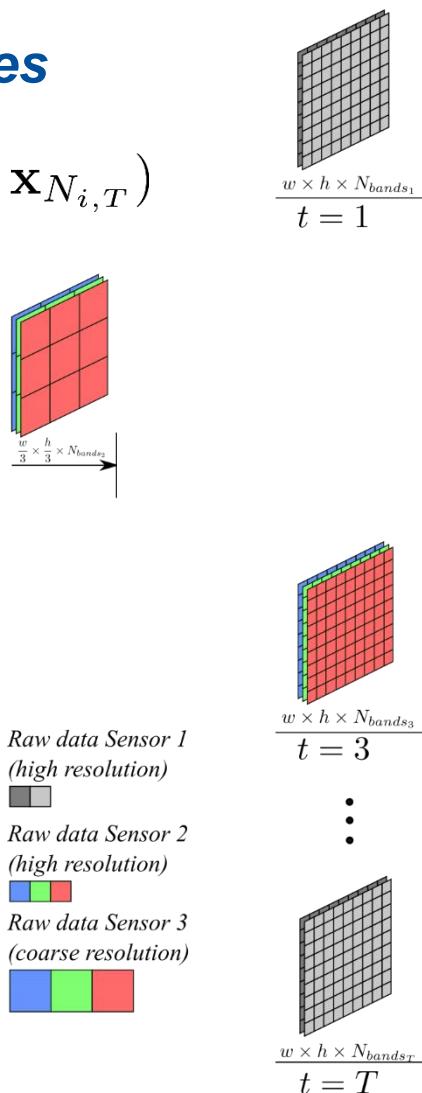
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Potencial de Asociación

CNN usando el stack de todas las imágenes

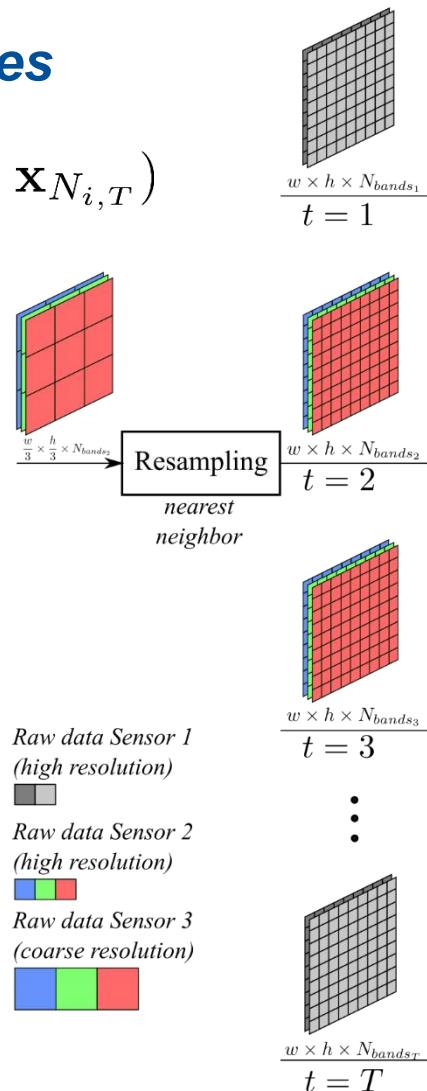
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Potencial de Asociación

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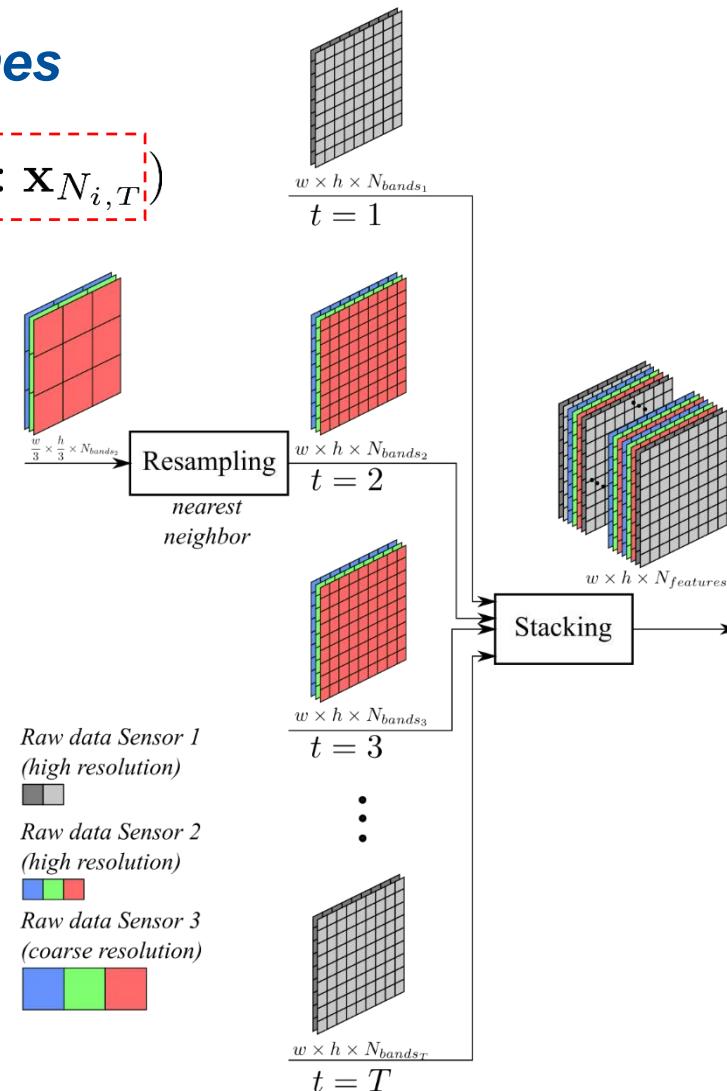
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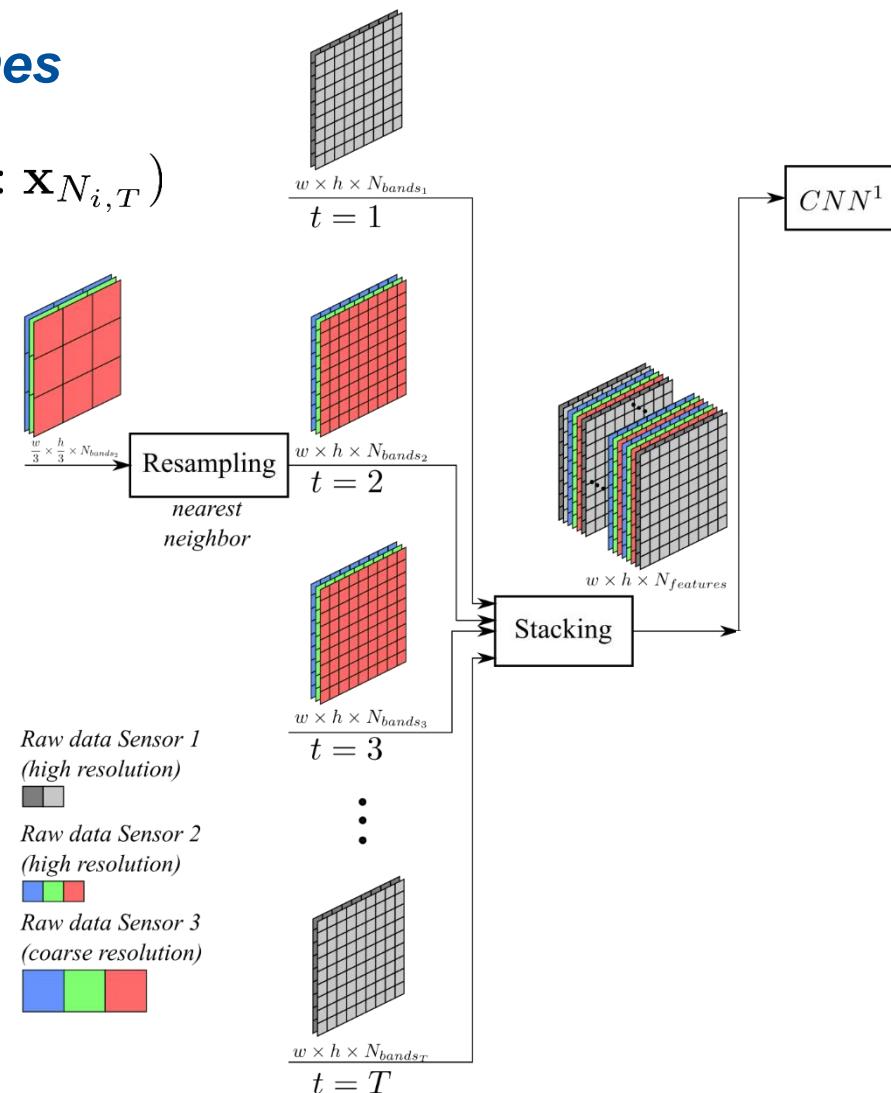
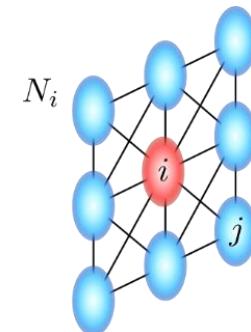


- Raw data Sensor 1
(high resolution)
Raw data Sensor 2
(high resolution)
Raw data Sensor 3
(coarse resolution)

Potencial de Asociación

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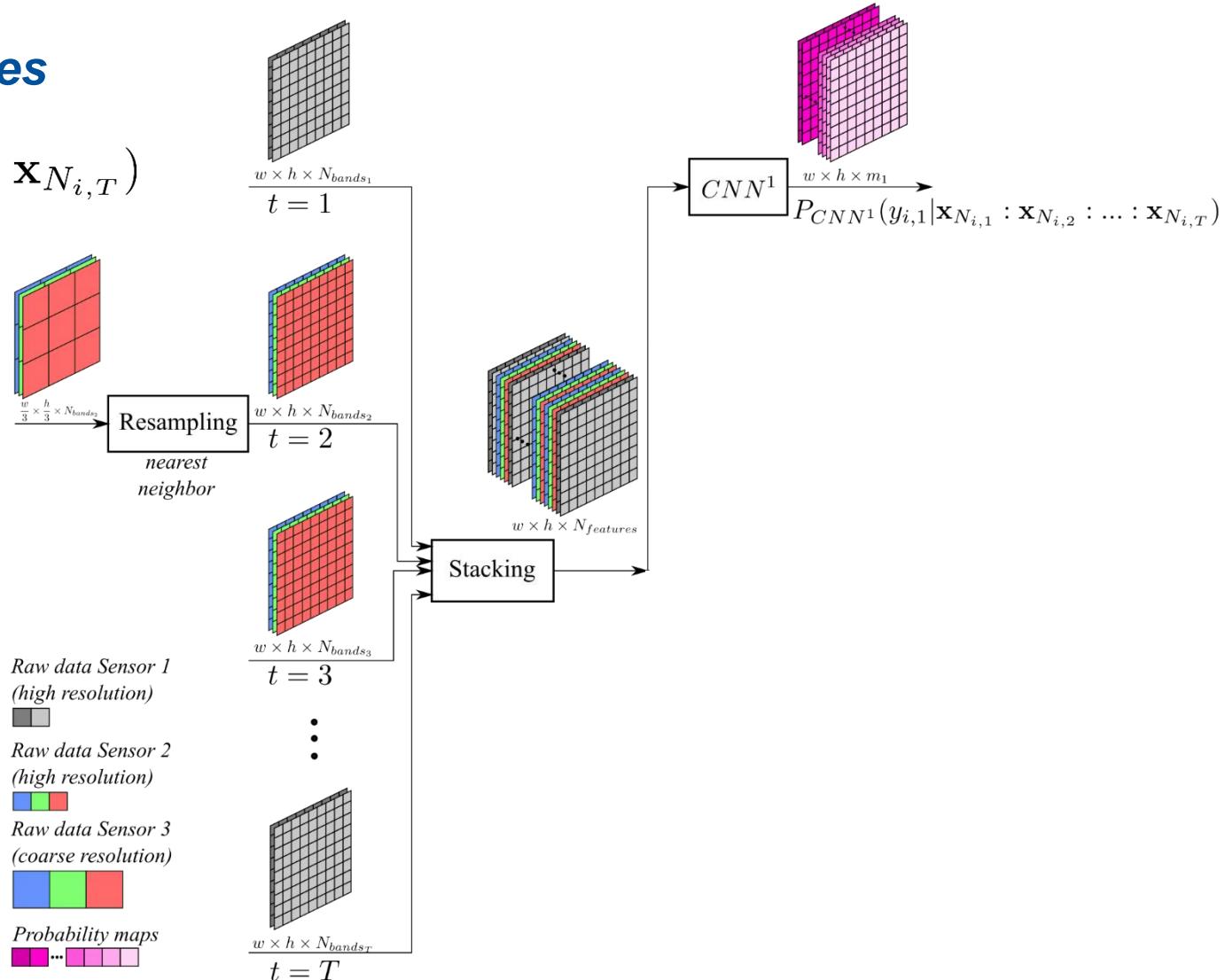
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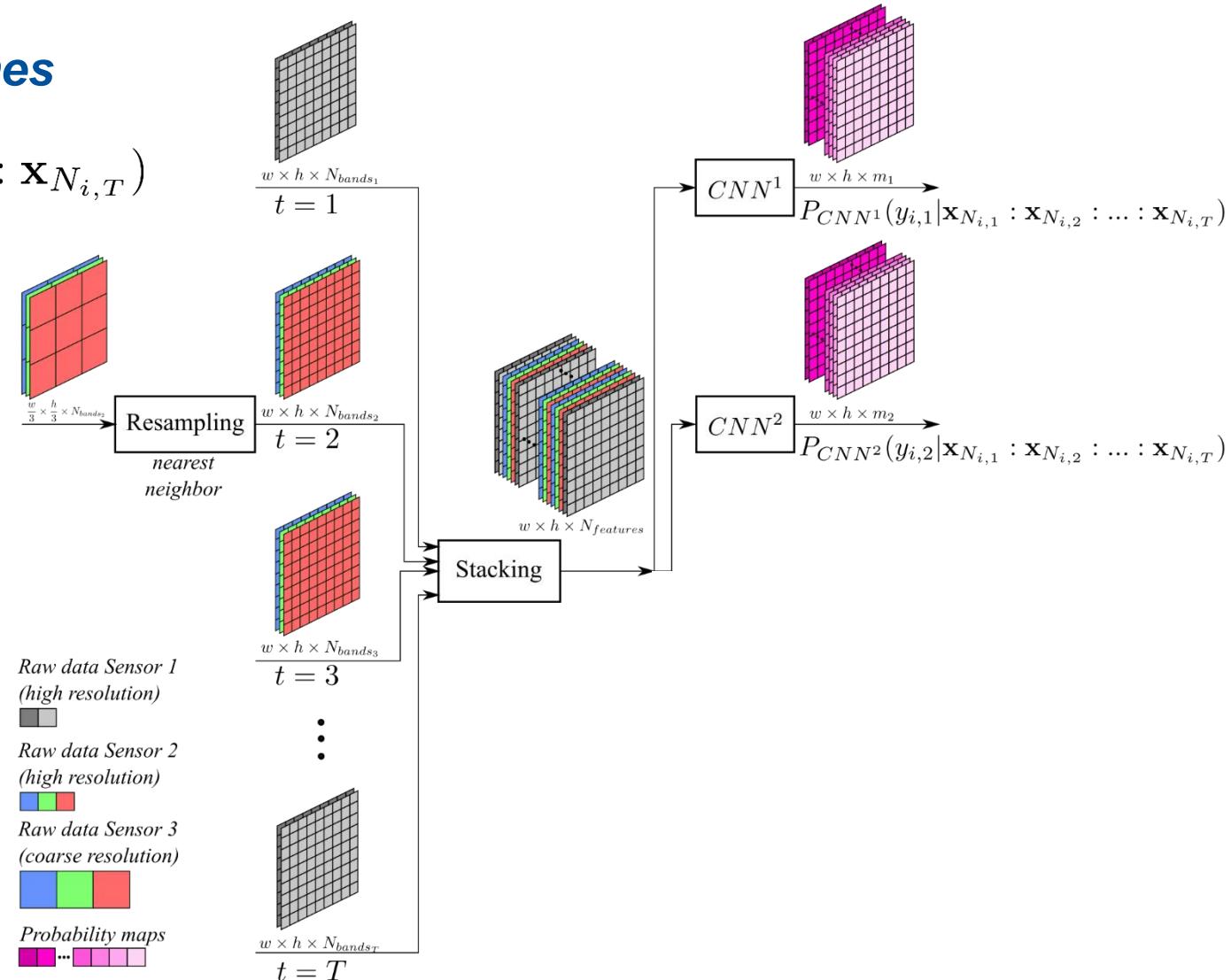
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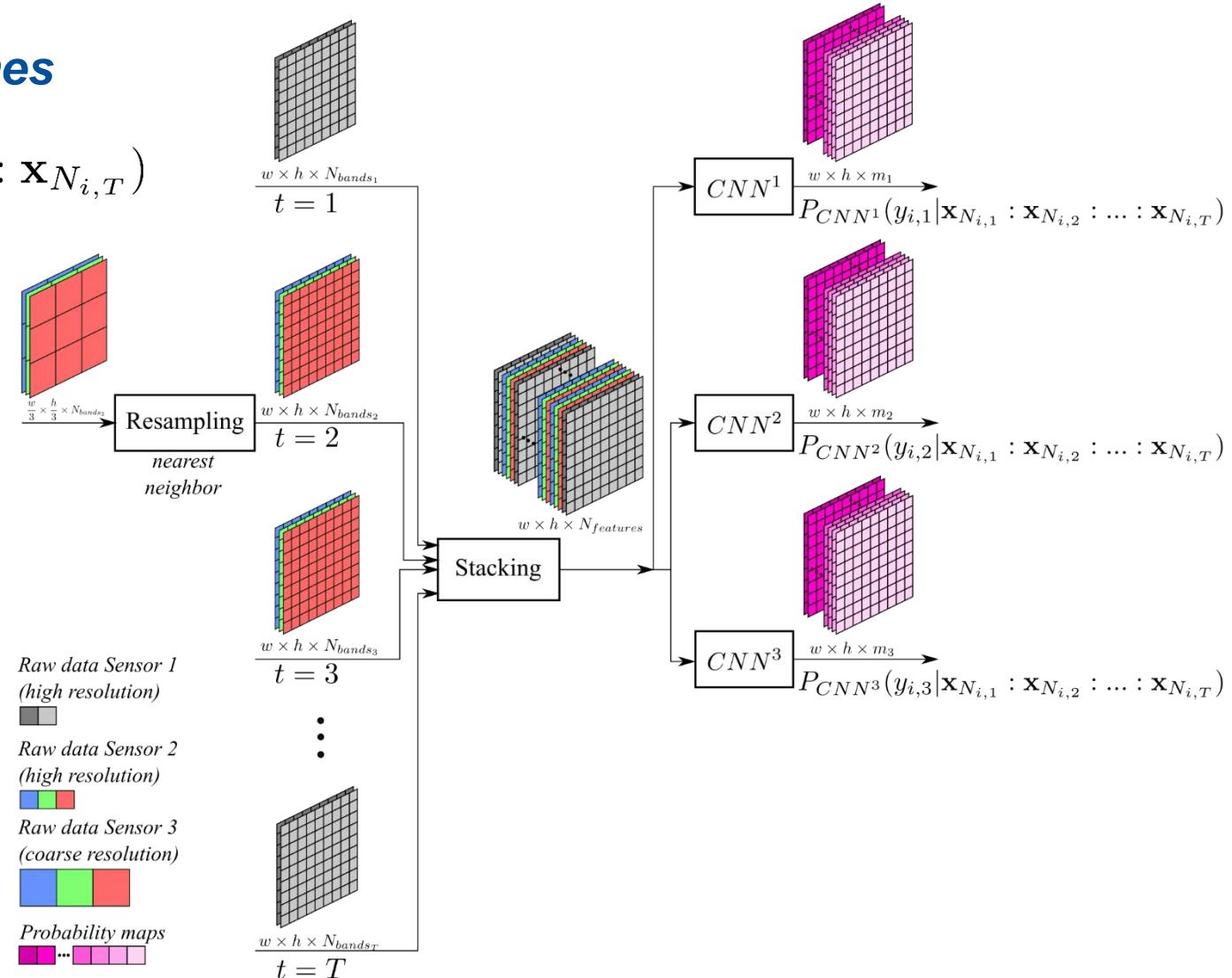
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Potencial de Asociación

CNN usando el stack de todas las imágenes

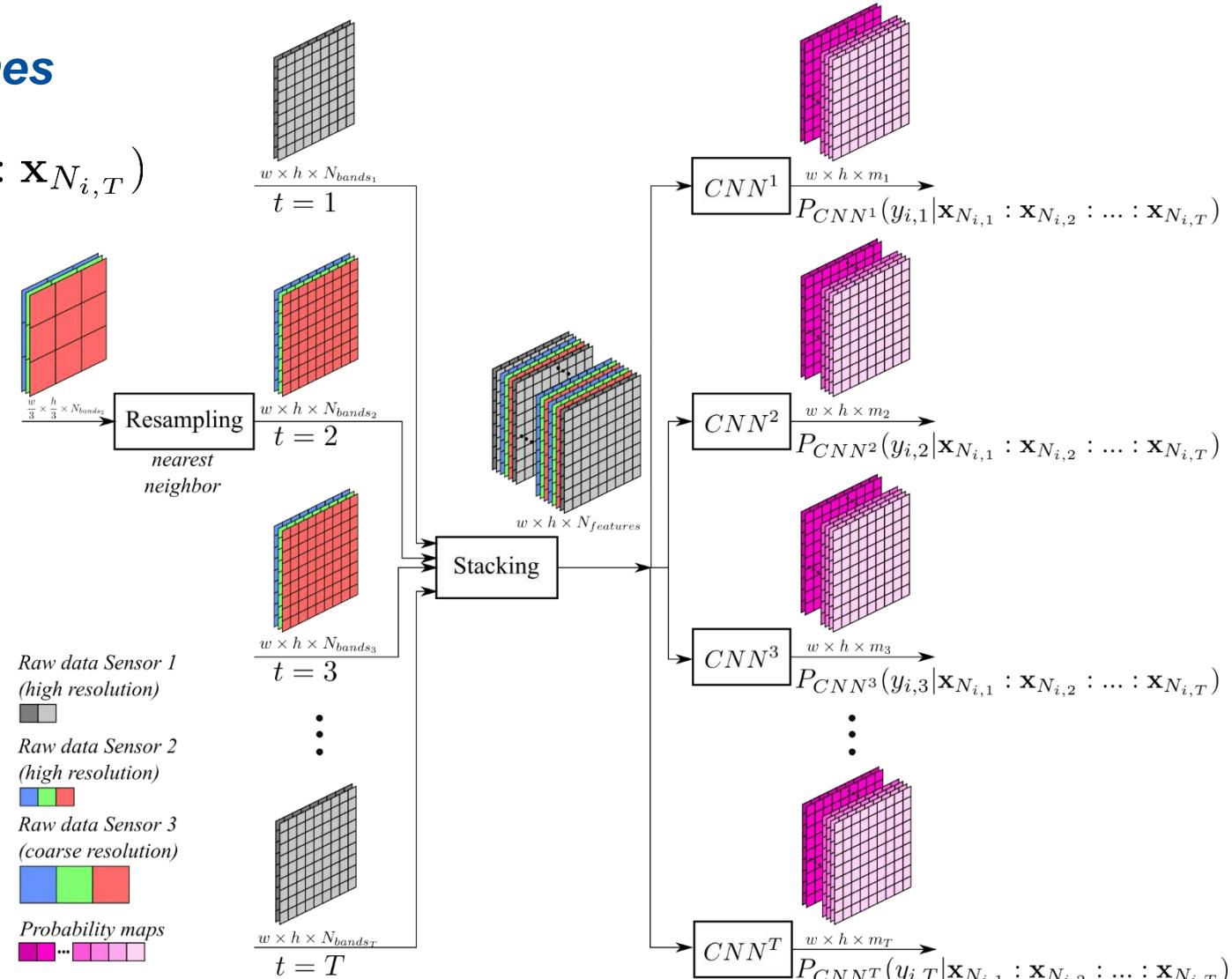
$$AP^t(y_{i,t}, \mathbf{x}) = \log P_{CNN^t}(y_{i,t} | \mathbf{x}_{N_{i,1}} : \mathbf{x}_{N_{i,2}} : \dots : \mathbf{x}_{N_{i,T}})$$



Potencial de Asociación

CNN usando el stack de todas las imágenes

$$AP^t(y_{i,t}, \mathbf{x}) = \log P_{CNN^t}(y_{i,t} | \mathbf{x}_{N_{i,1}} : \mathbf{x}_{N_{i,2}} : \dots : \mathbf{x}_{N_{i,T}})$$



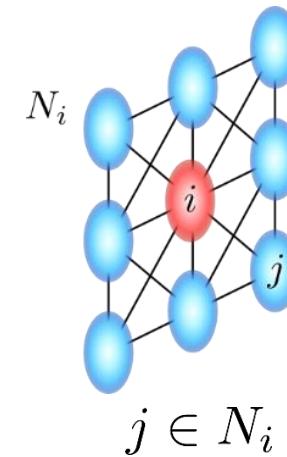
Modelo Contrast-sensitive Potts

$$SIP^t(y_{i,t}, y_{j,t}, \mathbf{x}_{i,t}, \mathbf{x}_{j,t}) = \begin{cases} p + (1-p)e^{-d_{i,j,t}^2/2\sigma_t^2} & , y_{i,t} = y_{j,t} \\ 0 & , y_{i,t} \neq y_{j,t} \end{cases}$$

donde: $d_{ij,t} = \|\mathbf{g}_{i,t}(\mathbf{x}_{i,t}) - \mathbf{g}_{j,t}(\mathbf{x}_{j,t})\|$

σ^2 valor medio del cuadrado de $d_{ij,t}$

$p \in [0, 1]$ controla la influencia relativa de los términos dependientes e independientes de los datos.

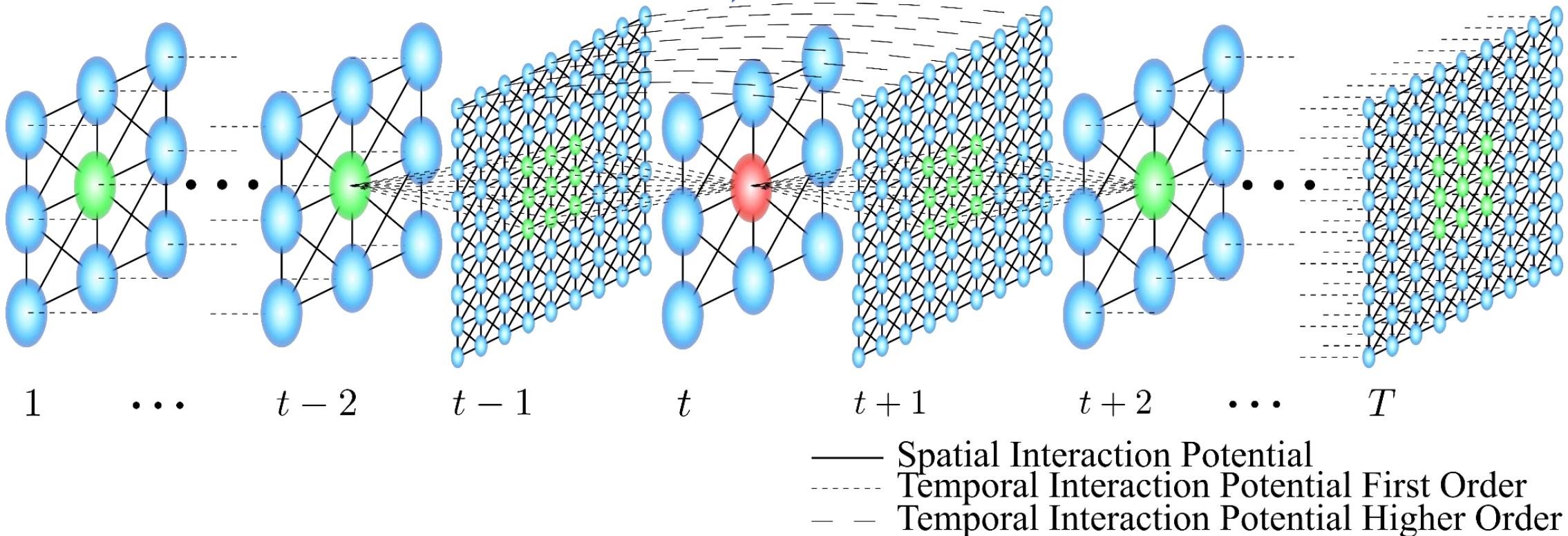


$j \in N_i$

Potencial de Interacción Temporal

Conecciones de orden mayor

$$TIP^{tk}(y_{i,t}, y_{i,k}) = \begin{bmatrix} (\)_{11} & (\)_{12} & \dots & (\)_{1m_k} \\ (\)_{21} & (\)_{22} & \dots & (\)_{2m_k} \\ \vdots & \vdots & \ddots & \vdots \\ (\)_{m_t 1} & (\)_{m_t 2} & \dots & (\)_{m_t m_k} \end{bmatrix}_{m_t \times m_k}$$



Outline

1. Introducción

2. CRFs

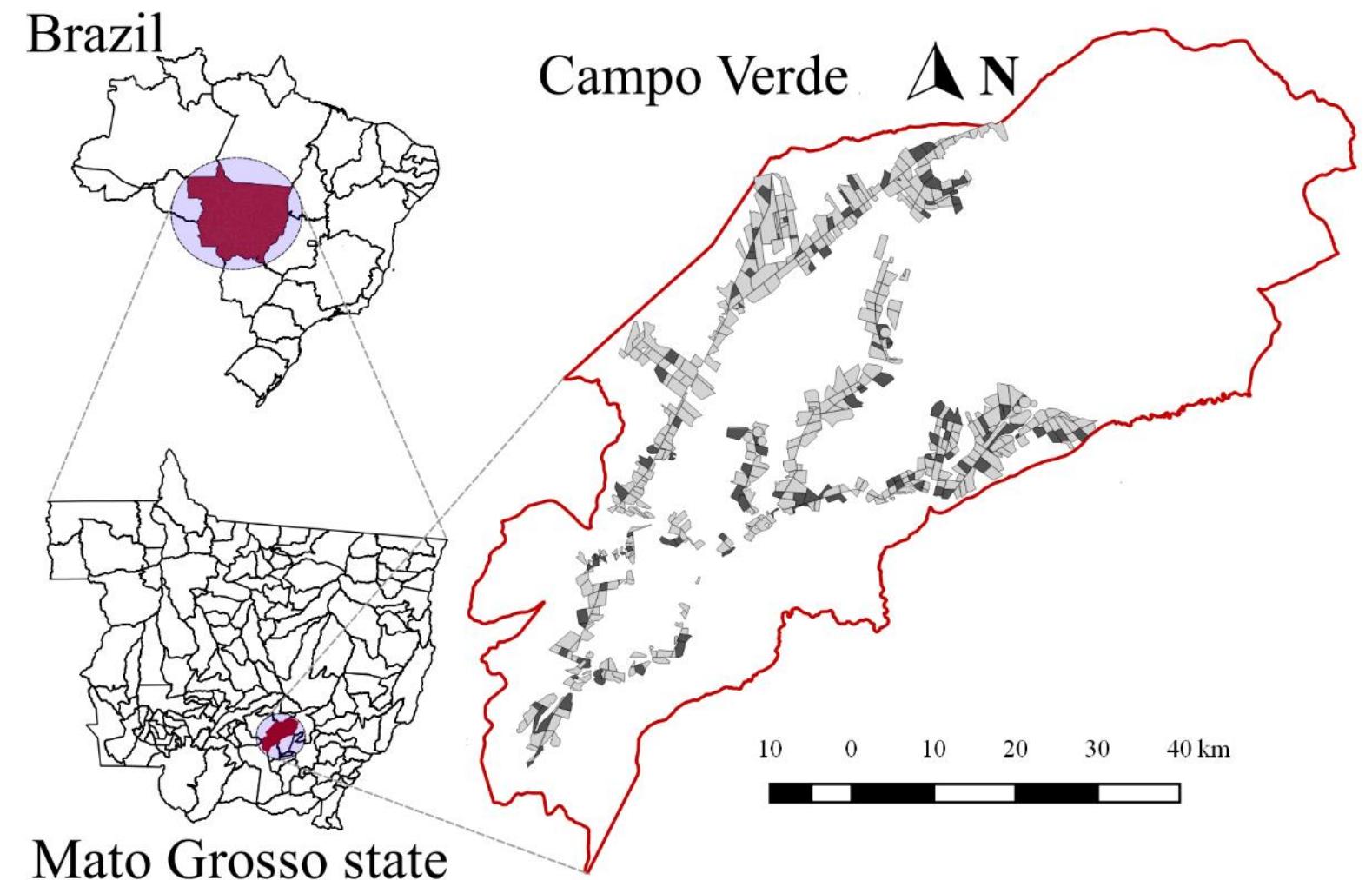
3. Resultados

4. Conclusiones

Dataset

Campo Verde

- Mato Grosso, Brasil



Campo Verde

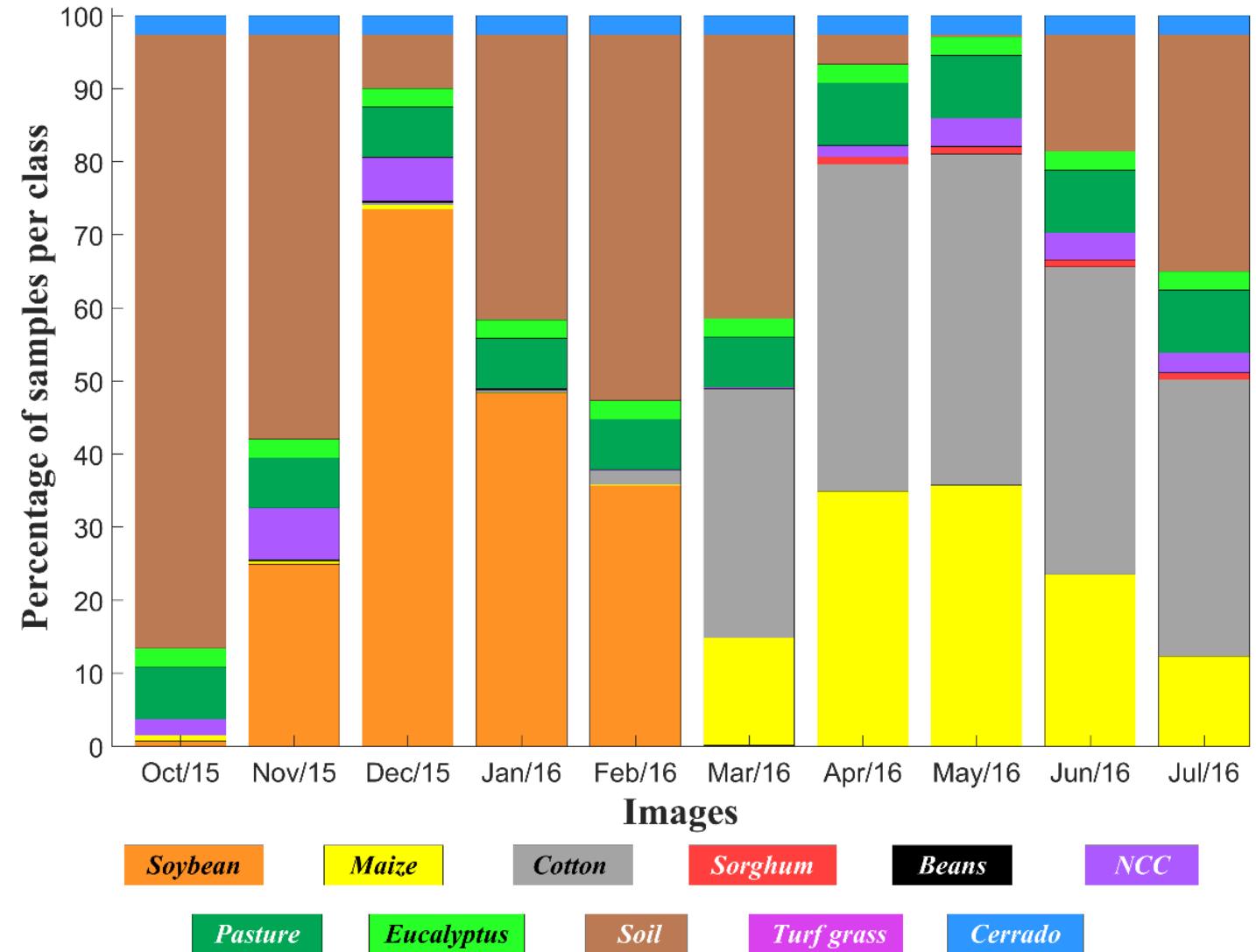
- Mato Grosso, Brasil
- 14 Sentinel-1A / 5 Landsat 8

Year	Month	Date	
		Sentinel-1A	Landsat 8
2015	October	29	-
	November	10, 22	11
	December	04, 16	-
2016	January	21	-
	February	14	-
	March	09, 21	-
	April	-	19
	May	08, 20	05
	June	13	
	July	07, 31	08, 24

Dataset

Campo Verde

- Mato Grosso, Brasil
- 14 Sentinel-1A / 5 Landsat 8
- Desde Octubre 2015 hasta Julio 2016



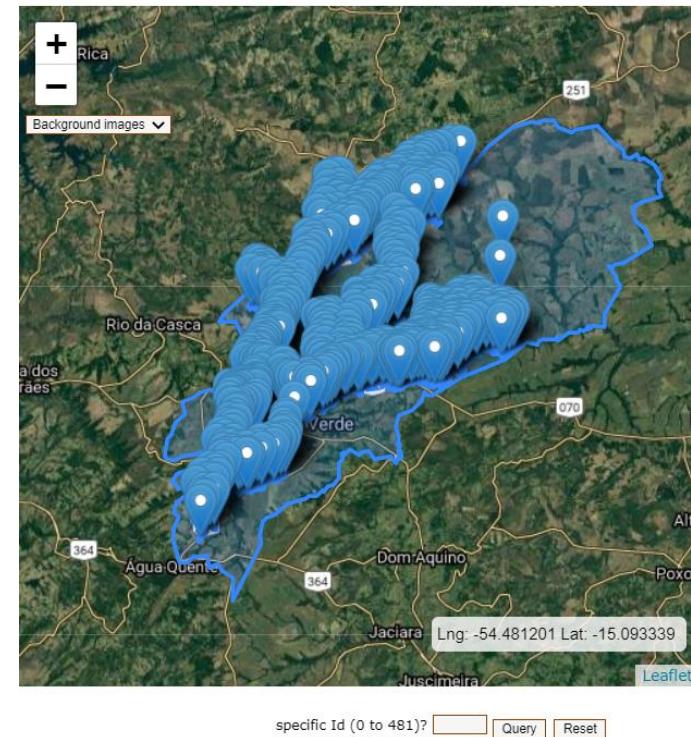
Campo Verde

- Mato Grosso, Brasil
- 14 Sentinel-1A / 5 Landsat 8
- Desde Octubre 2015 hasta Julio 2016
- Train/Test: 20% / 80%

Dataset

Campo Verde

- Mato Grosso, Brasil
- 14 Sentinel-1A / 5 Landsat 8
- Desde Octubre 2015 hasta Julio 20
- Train/Test: 20% / 80%



Disponible en:

<http://www.obt.inpe.br/agricultural-database/campoverde/>



Campo Verde Database

Data Field 58 Reference data (download) Sentinel-1 data (download) Landsat-8/OLI data (download) Photos Reference paper People involved Financial support

These photographs were taken during two field campaigns conducted in Campo Verde municipality between 14th-18th December 2015 and 9th-13th May 2016.



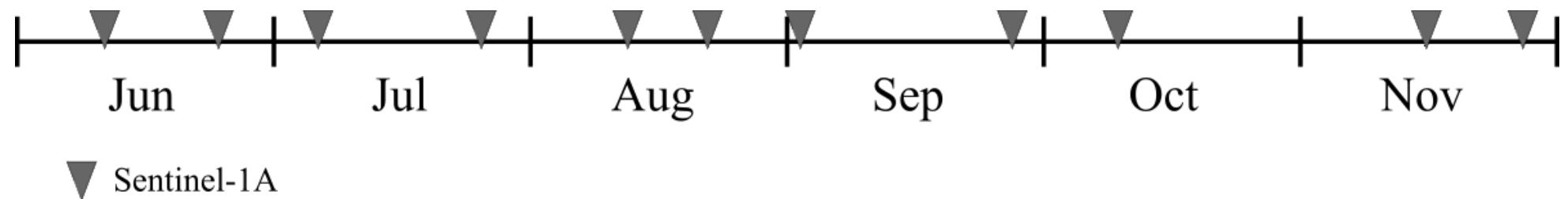
< Prev Next >

Protocolo Experimental

- 2 tipos de secuencias de imágenes:
 - **1 sensor:** SAR (Sentinel-1A)
 - **Múltiples sensores:** SAR (Sentinel-1A) + Óptico (Landsat 8)

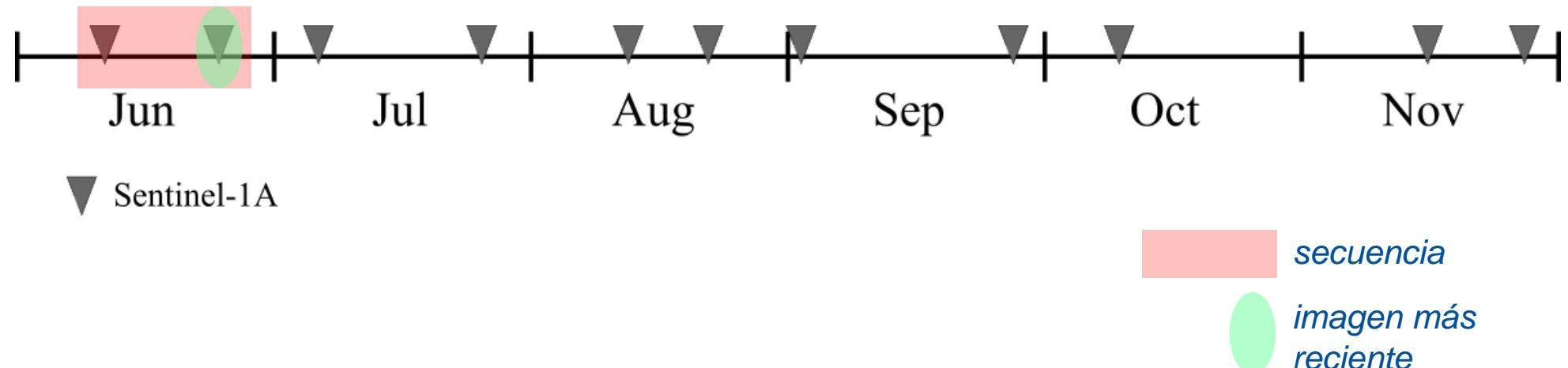
Protocolo Experimental

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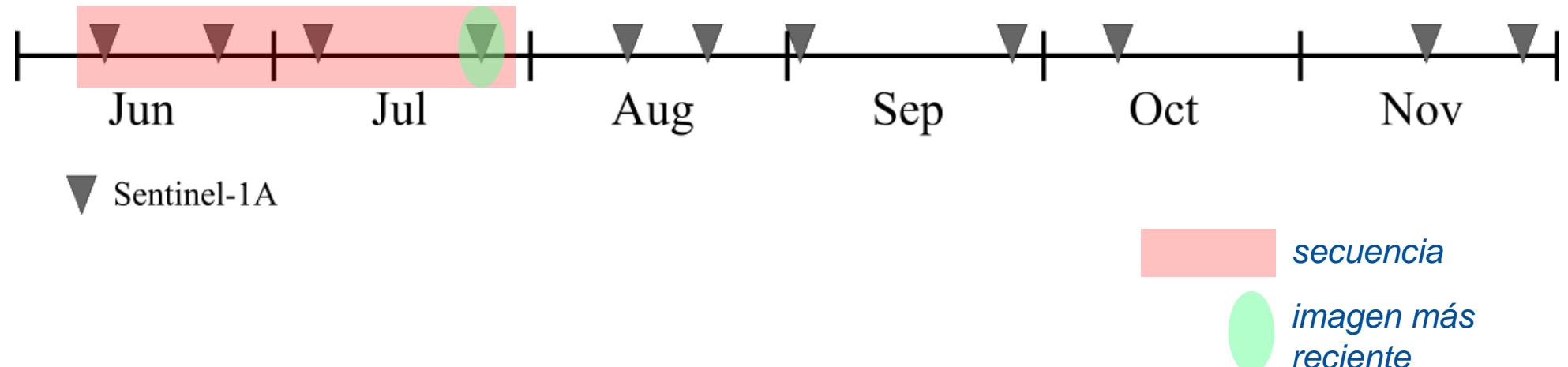
Protocolo Experimental

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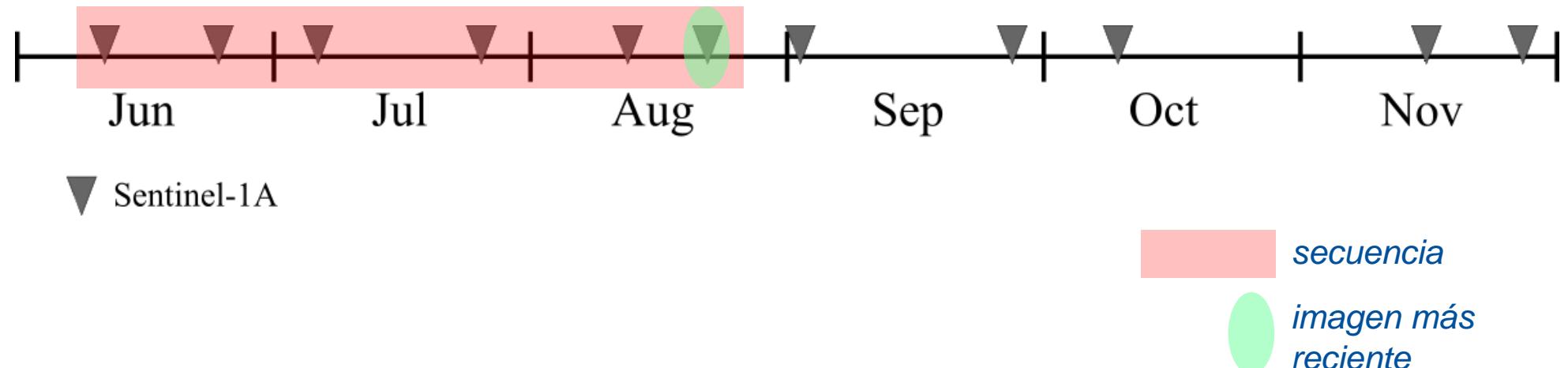
Protocolo Experimental

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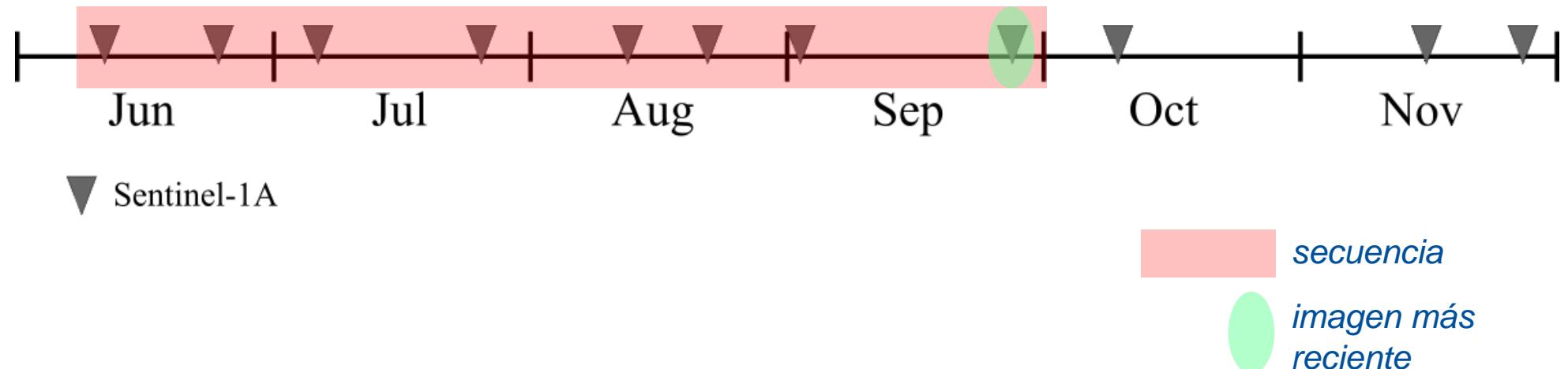
Protocolo Experimental

- 2 tipos de secuencias de imágenes:
 - 1 sensor: SAR (Sentinel-1A)
 - Múltiples sensores: SAR (Sentinel-1A) + Óptico (Landsat 8)



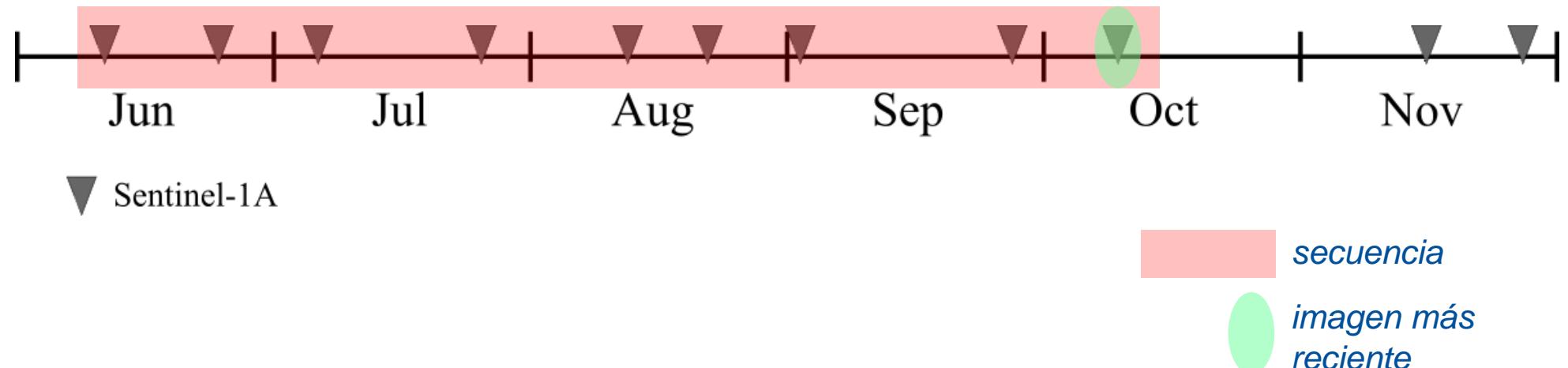
Protocolo Experimental

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 - 1 sensor: SAR (Sentinel-1A)
 - Múltiples sensores: SAR (Sentinel-1A) + Óptico (Landsat 8)



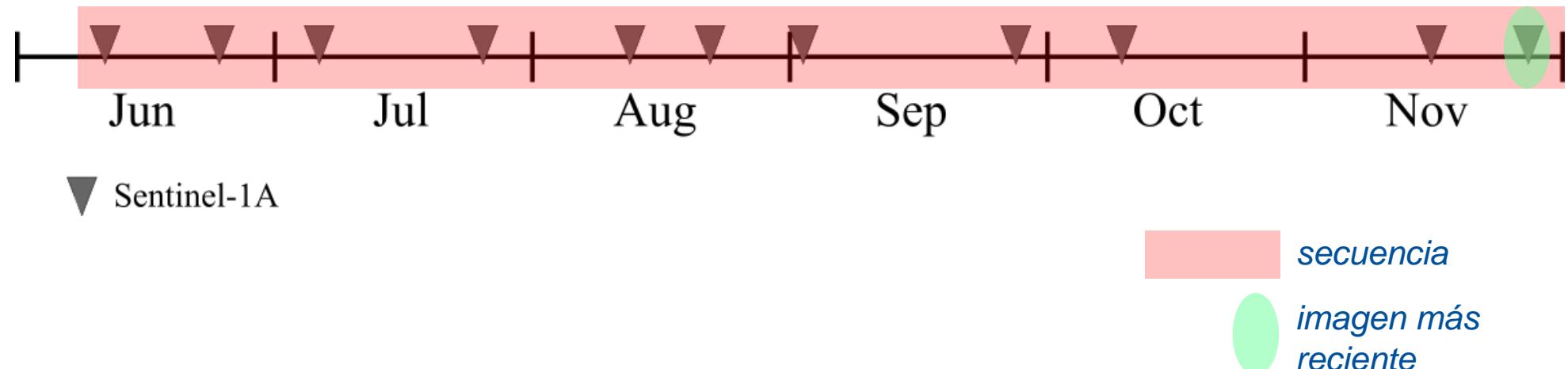
Protocolo Experimental

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 - Múltiples sensores: SAR (Sentinel-1A) + Óptico (Landsat 8)



Protocolo Experimental

- 2 tipos de secuencias de imágenes:
 - 1 sensor: SAR (Sentinel-1A)
 - Múltiples sensores: SAR (Sentinel-1A) + Óptico (Landsat 8)



Configuración Experimental

- **Random Forest (RF)**: 250 arboles, profundidad máxima 25
 - **Sentinel-1A (SAR)**
 - Correlación, homogeneidad, media y varianza (GLCM)
 - Direcciones: 0°, 45°, 90° y 135°, ventanas de 3 × 3
 - 2 polarizaciones: VV y VH
 - Dimensión de vector de atributos: 32
 - **Landsat 8 (Optical)**
 - Bandas: 1, 2, 3, 4, 5, 6 y 7
 - NDVI
 - Dimensión de vector de atributos: 8

Configuración Experimental

- **Convolutional Neural Network (CNN):**

Layer	Output Size
- Input	$9 \times 9 \times N_{features}$
- Convolutional Block (3×3 Conv., B.N. ⁷ , <i>Leaky ReLU</i>)	$9 \times 9 \times 80$
- Max Pooling (2×2)	$5 \times 5 \times 80$
- Convolutional Block (1×1 Conv., B.N., <i>Leaky ReLU</i>)	$5 \times 5 \times 80$
- Convolutional Block (3×3 Conv., B.N., <i>Leaky ReLU</i>)	$5 \times 5 \times 96$
- Max Pooling (2×2)	$3 \times 3 \times 96$
- Fully Connected	256
- B.N.	256
- <i>Leaky ReLU</i>	256
- Dropout	256
- <i>Softmax</i>	m_t

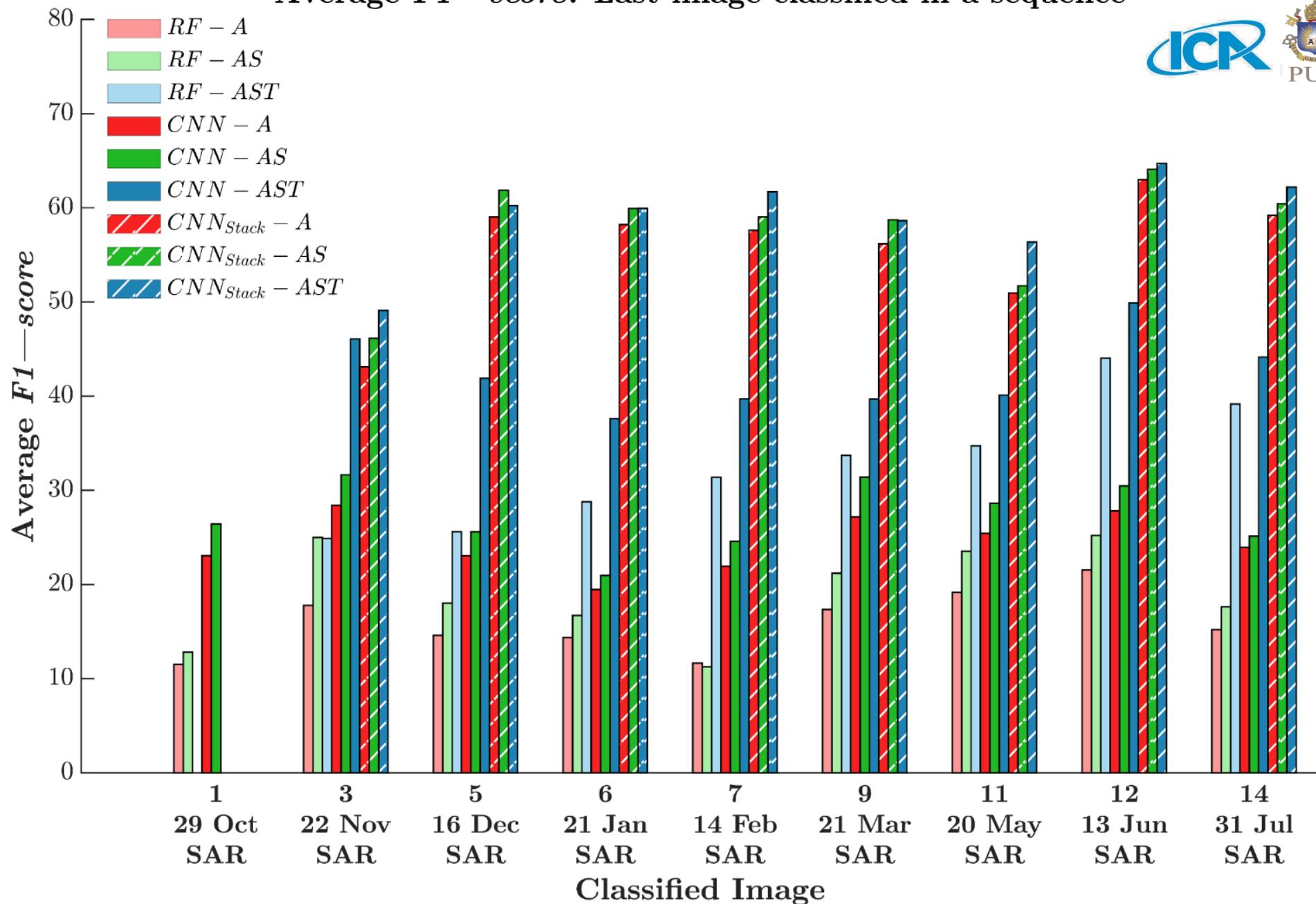
Configuración Experimental

- Para el CRF
 - **Inferencia**
 - Óptimo \hat{y} que maximiza $P(y|x)$
 - Sum-product Loopy Belief Propagation (LBP)
 - **Métricas**
 - *Overall Accuracy (OA)* y *average F1-score*

Resultados 1 sensor

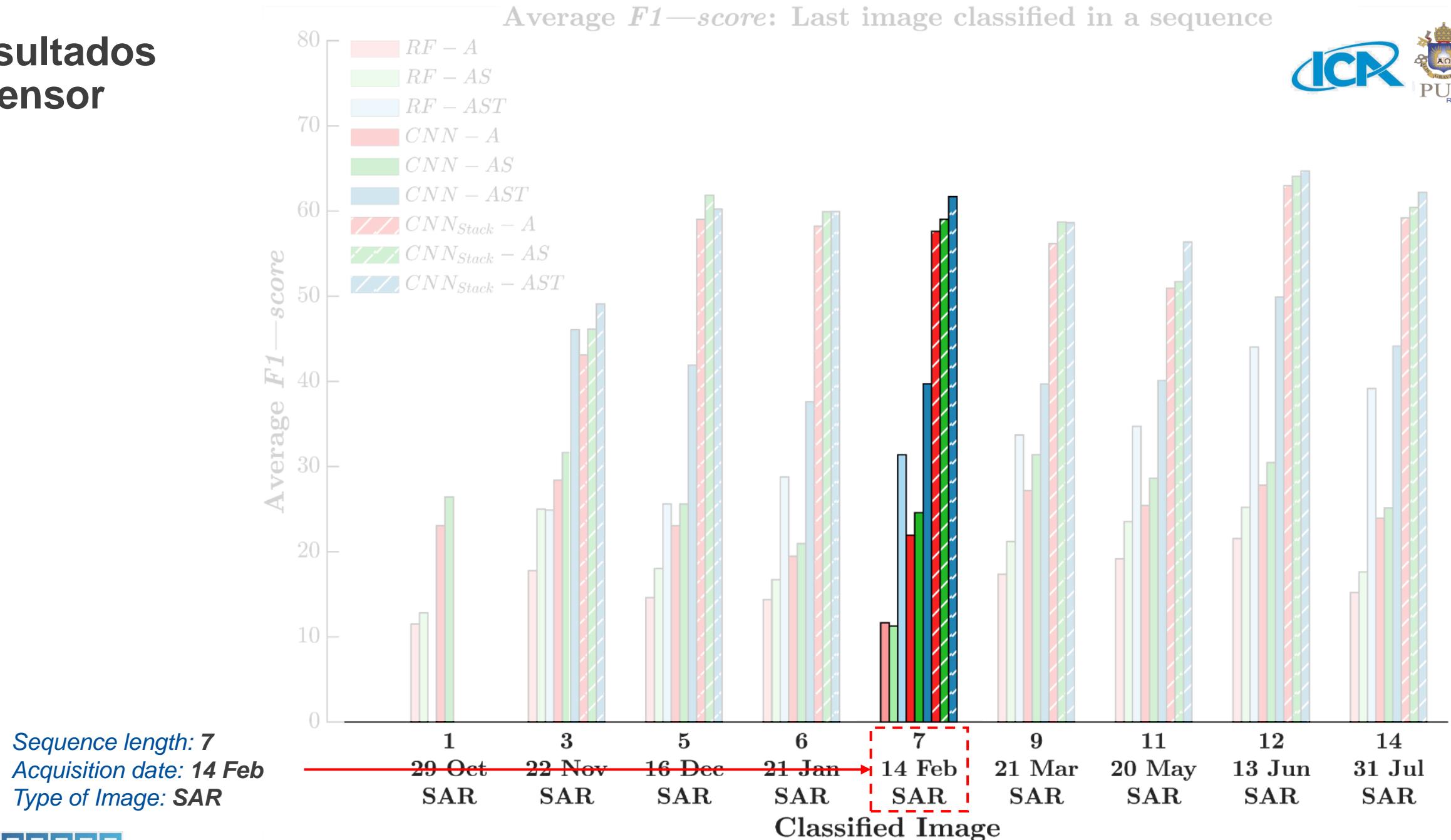
Resultados 1 sensor

Average $F1$ —score: Last image classified in a sequence



Resultados 1 sensor

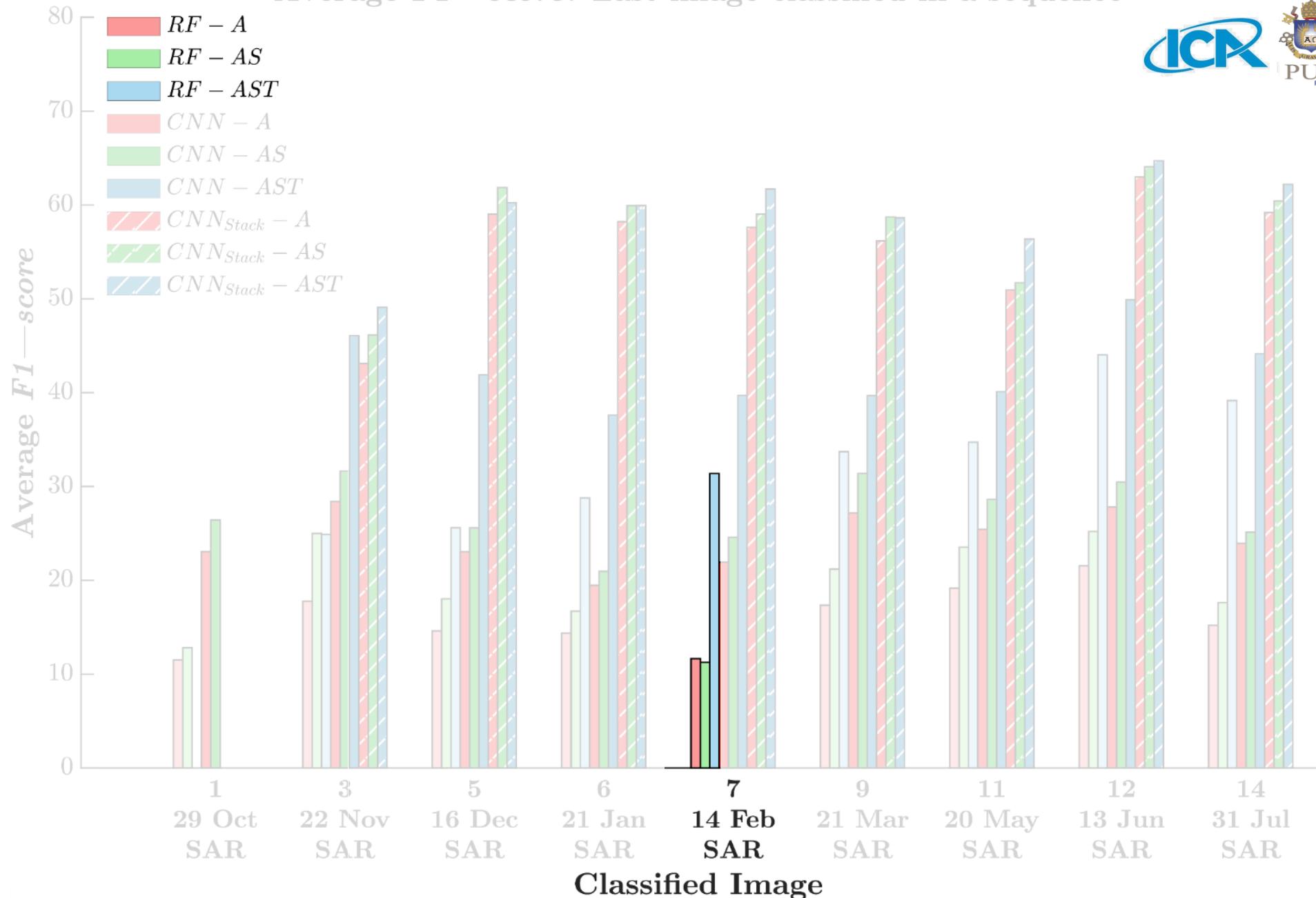
Average $F1-score$: Last image classified in a sequence



Resultados 1 sensor

Random Forest + GLCM

Average $F1-score$: Last image classified in a sequence



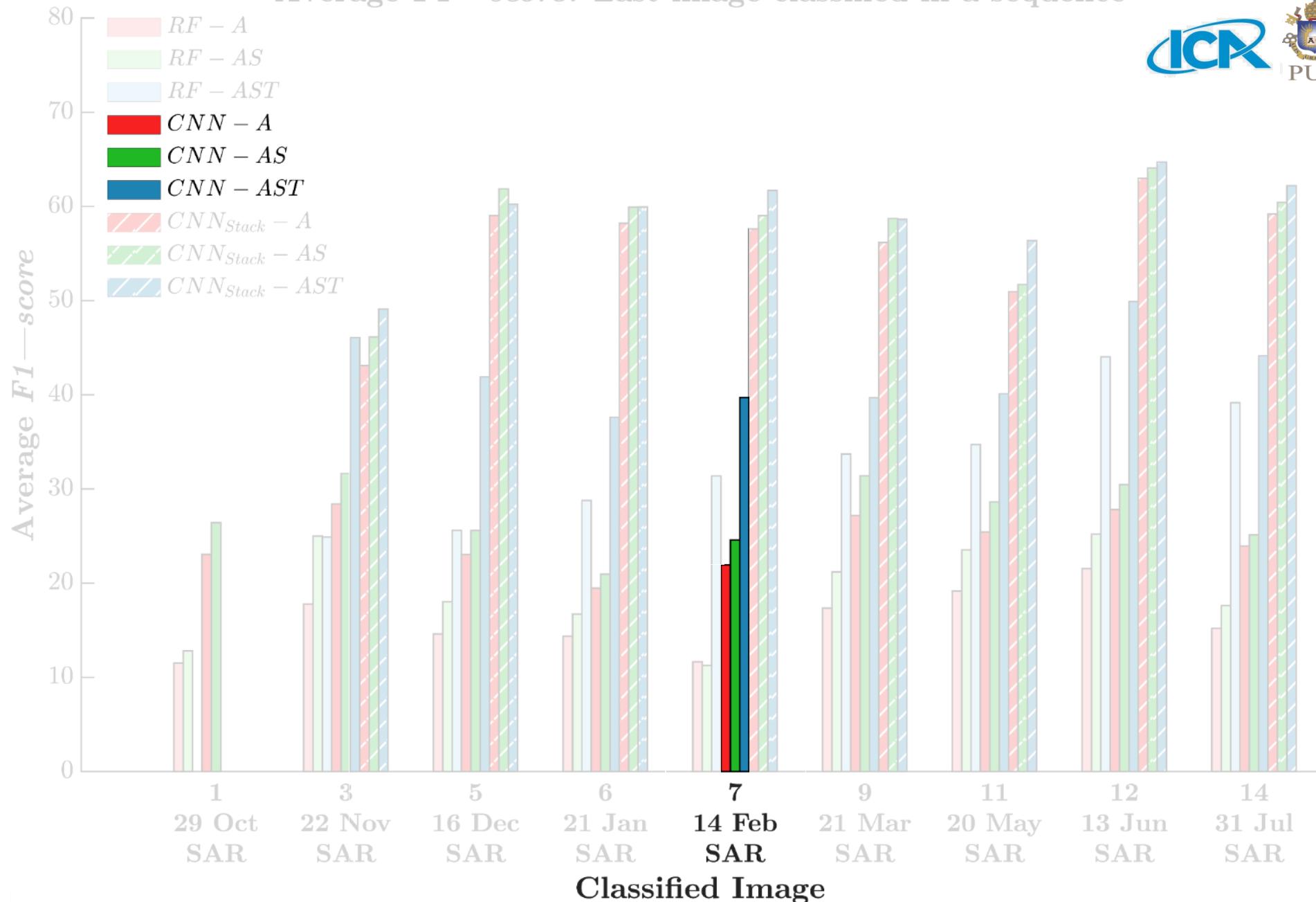
Classified Image

Pedro M. Achancaray Diaz

Resultados 1 sensor

CNN single image

Average *F1-score*: Last image classified in a sequence

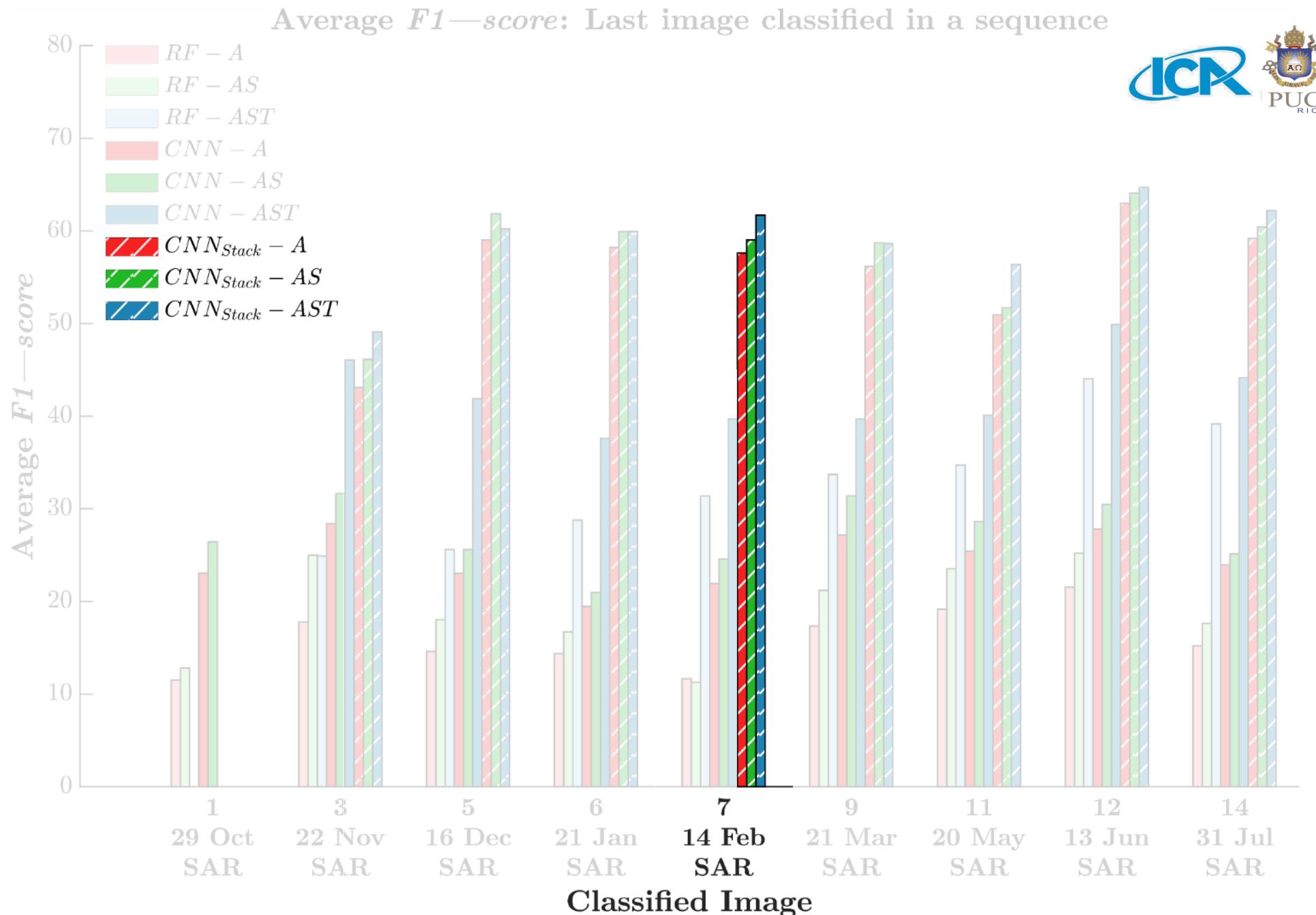


Classified Image

Pedro M. Achancaray Diaz

Resultados 1 sensor

CNN image stack

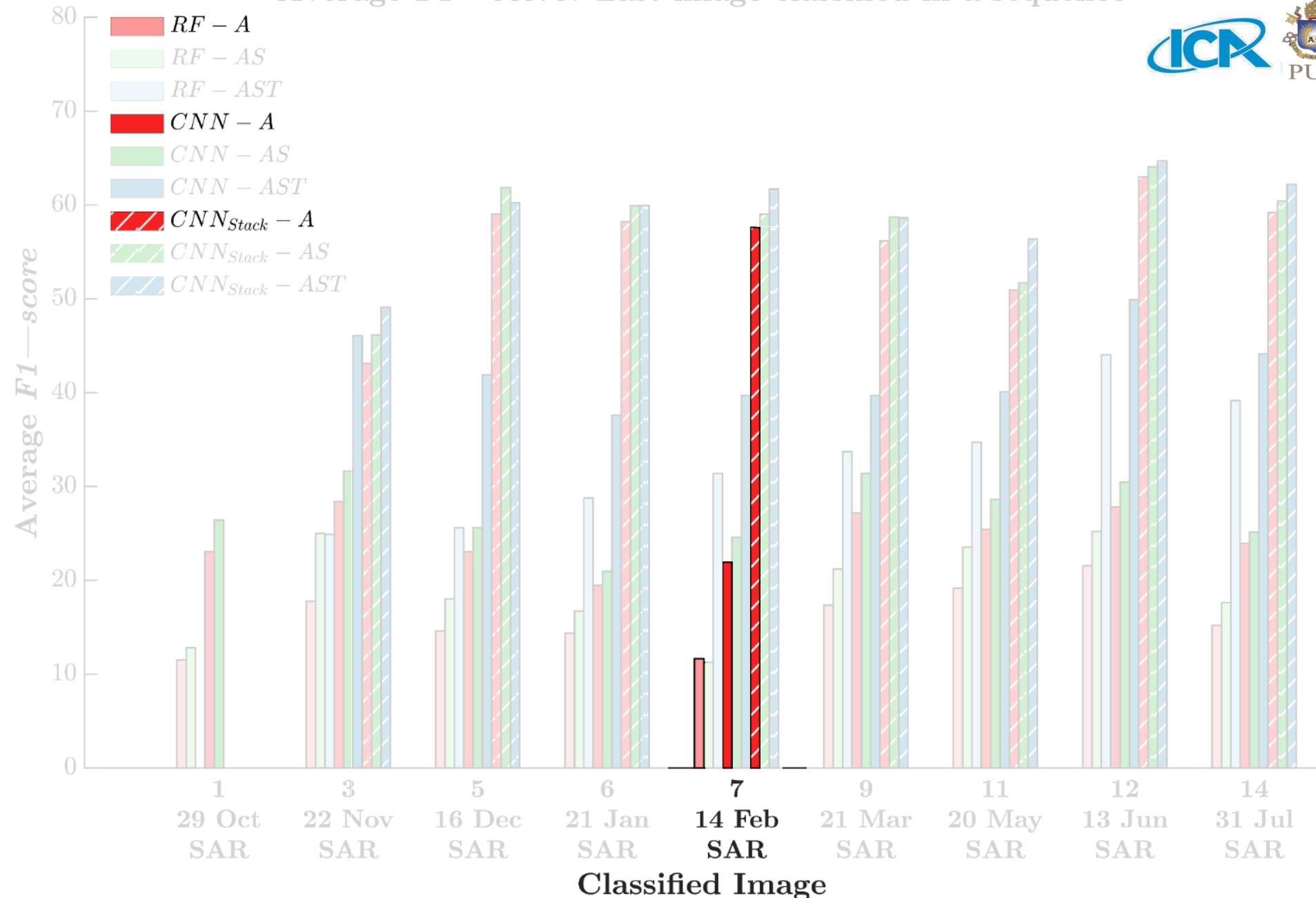


Pedro M. Achancaray Diaz

Resultados 1 sensor

Average $F1$ —score: Last image classified in a sequence

A: association potential

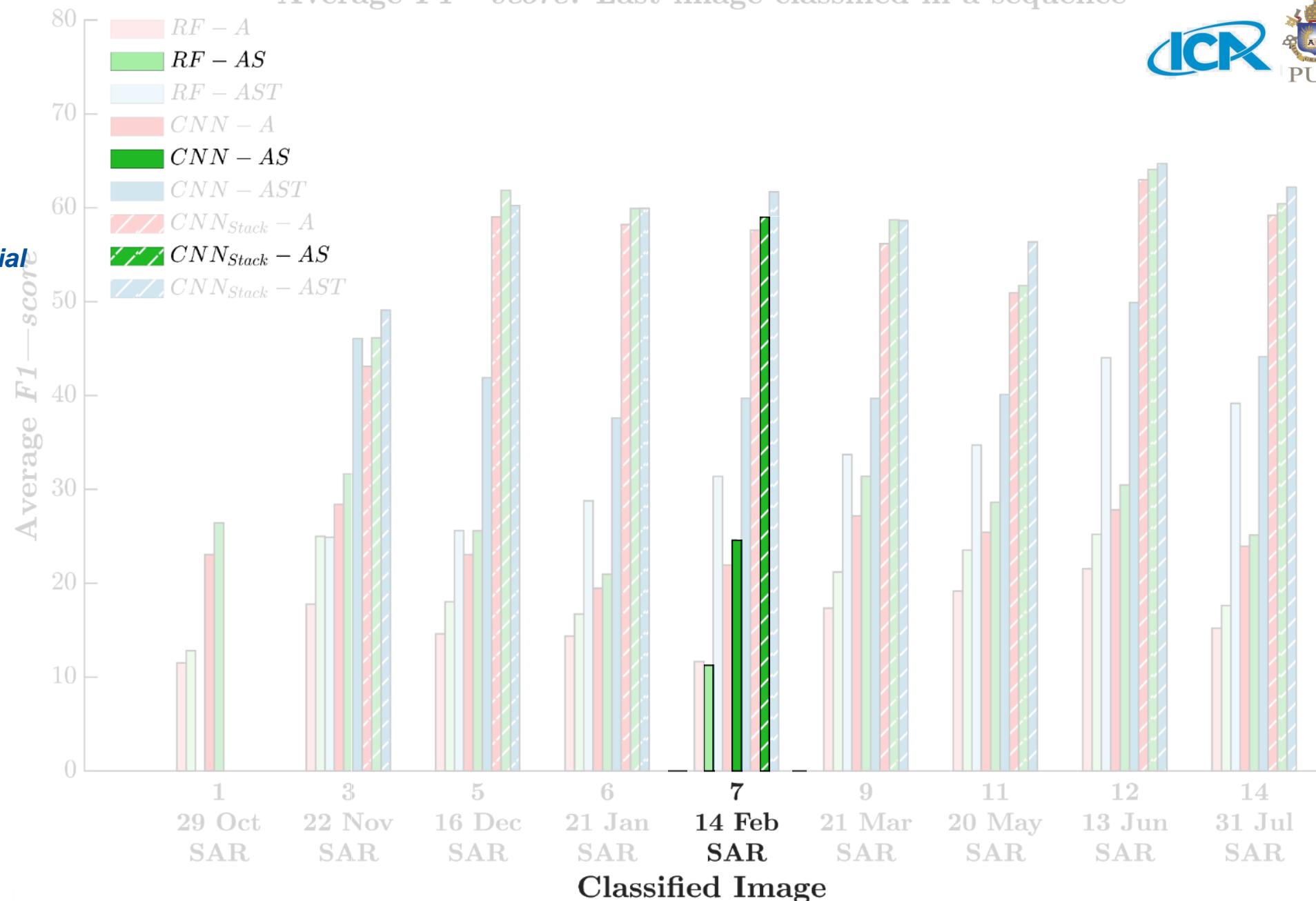


Resultados 1 sensor

Average $F1$ —score: Last image classified in a sequence

A: association potential

S: spatial interaction potential



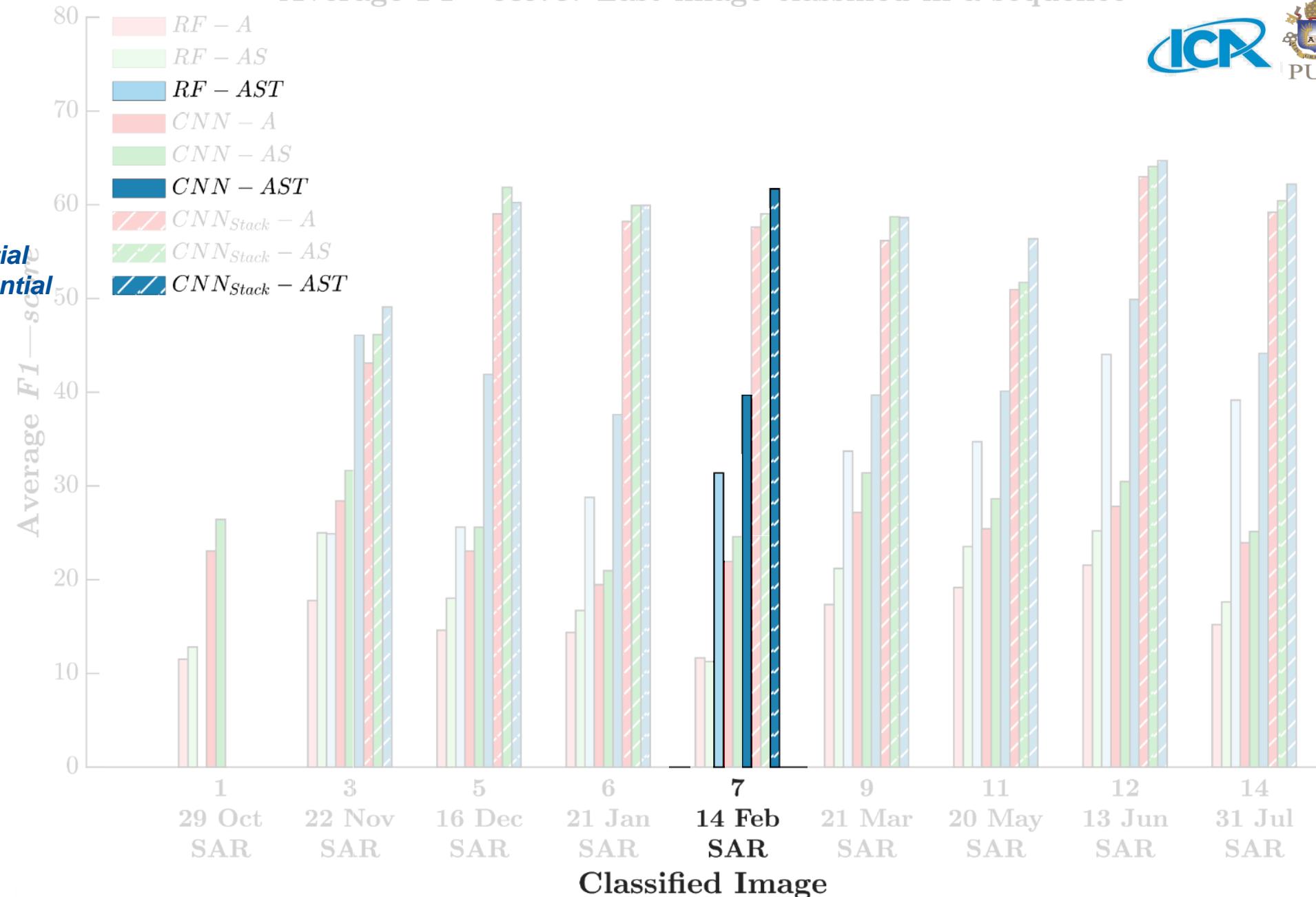
Classified Image

Pedro M. Achancaray Diaz

Resultados 1 sensor

Average $F1$ —score: Last image classified in a sequence

A: association potential
S: spatial interaction potential
T: temporal interaction potential



Classified Image

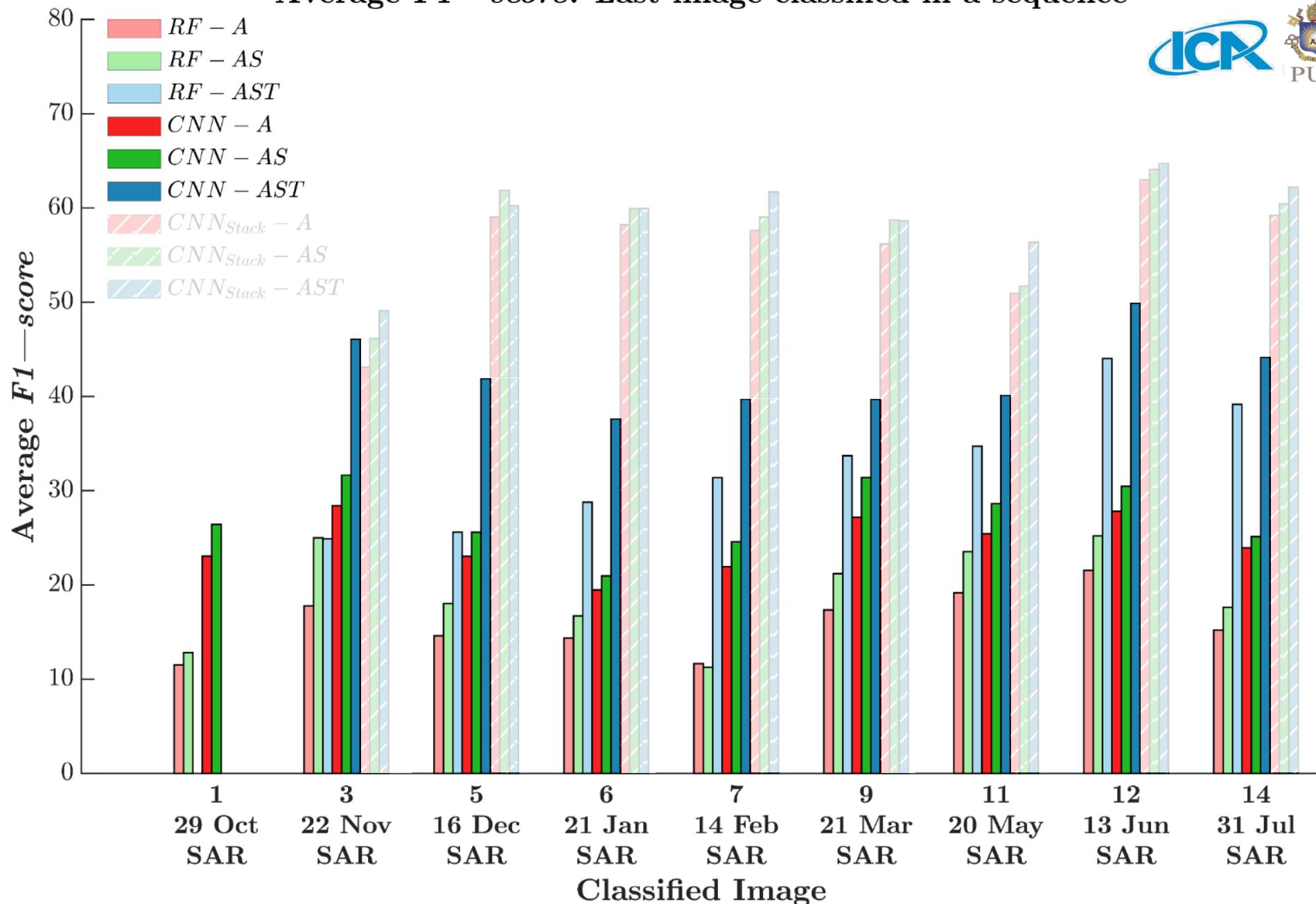
Pedro M. Achancaray Diaz

Resultados 1 sensor

RF + GLCM

CNN single image

Average $F1$ —score: Last image classified in a sequence

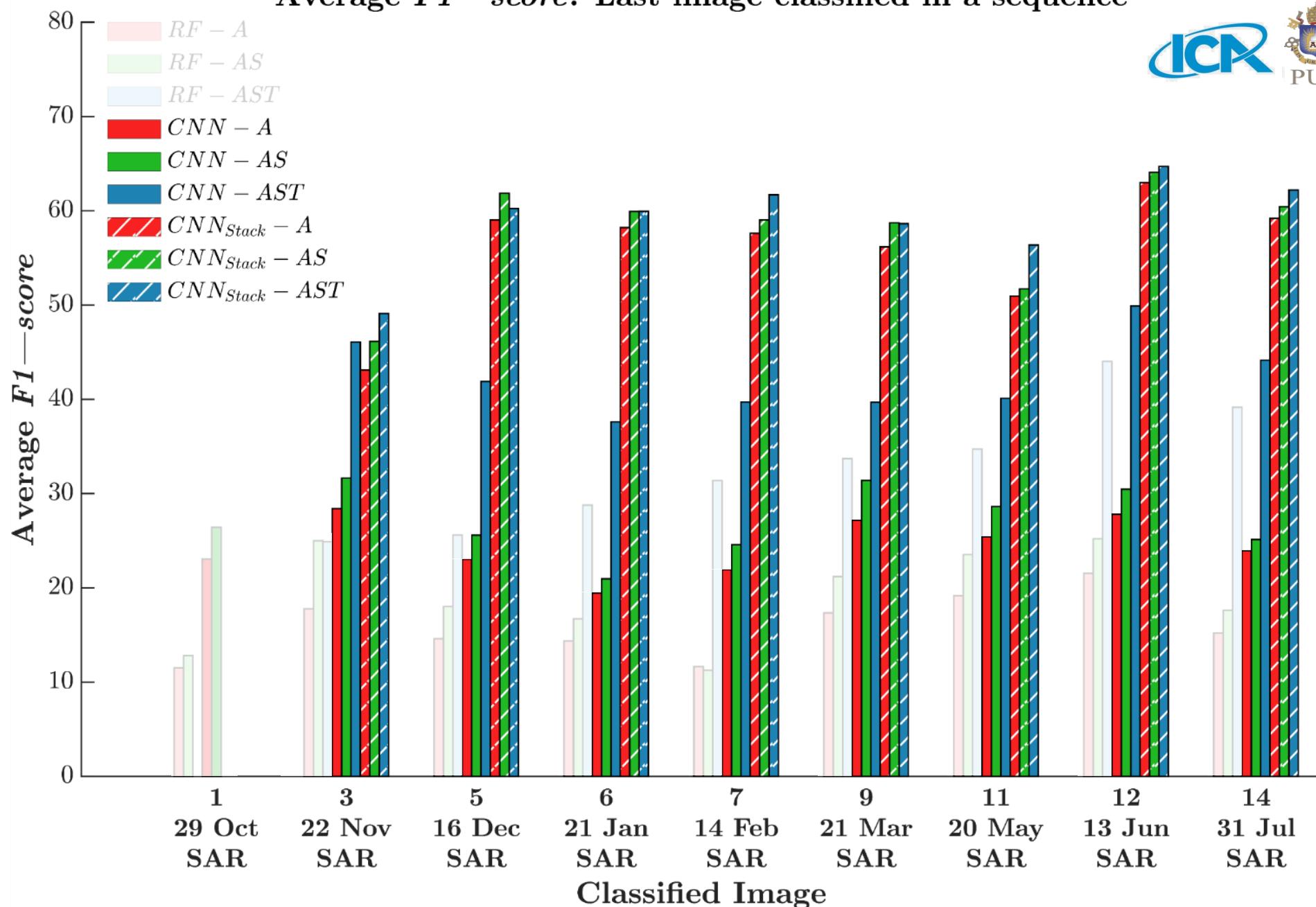


Resultados 1 sensor

CNN single image

CNN image stack

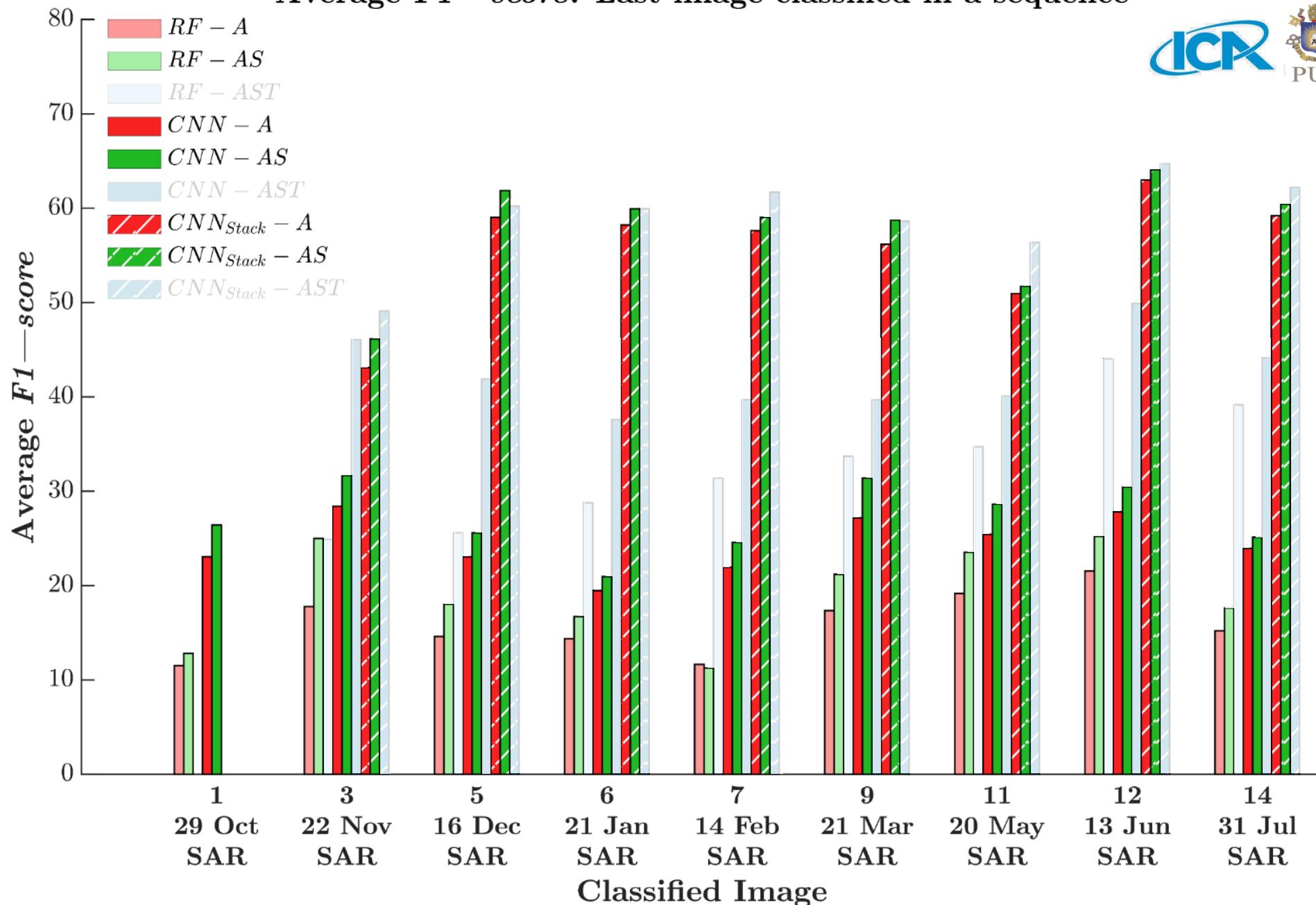
Average $F1$ —score: Last image classified in a sequence



Resultados 1 sensor

Introduction of the SIP

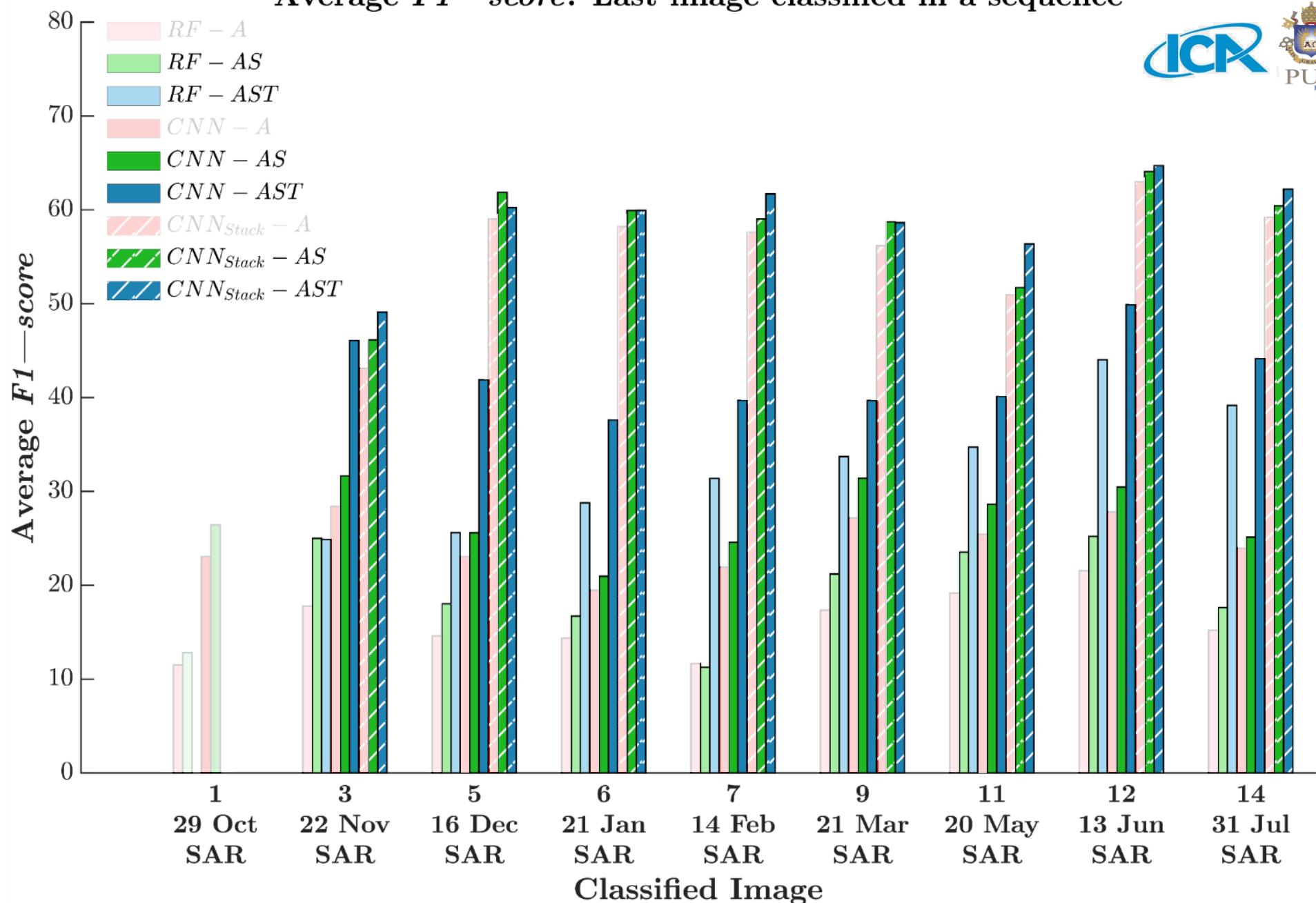
Average $F1$ —score: Last image classified in a sequence



Resultados 1 sensor

Introduction of the TIP

Average $F1$ —score: Last image classified in a sequence



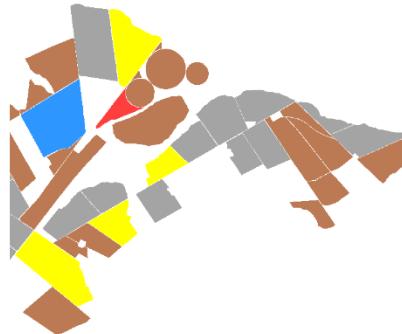
Resultados 1 sensor

Classification Maps

Sequence length: 14

Date: July 31st

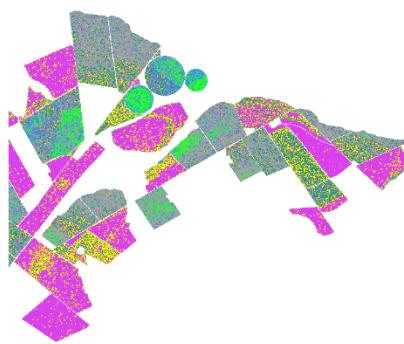
Sensor: SAR



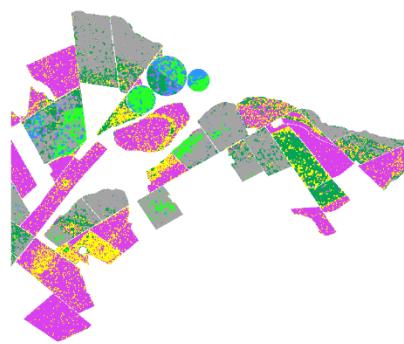
a) Reference

Classes:

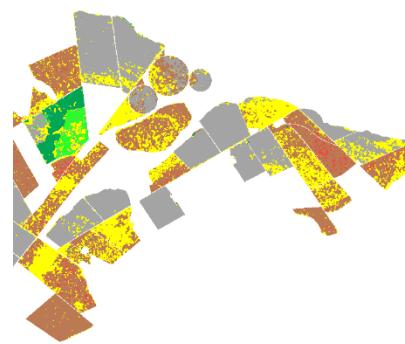
Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



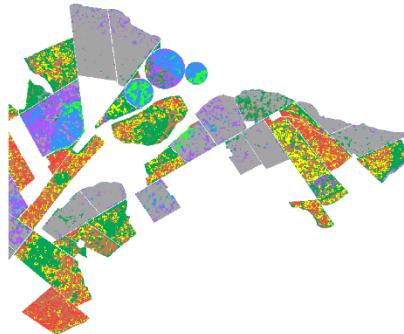
b) RF - A



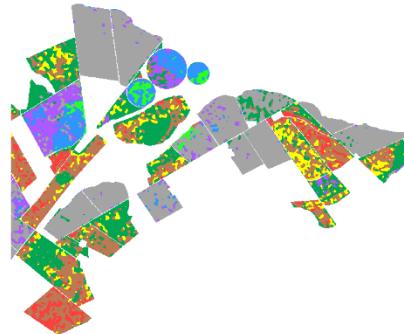
c) RF - AS



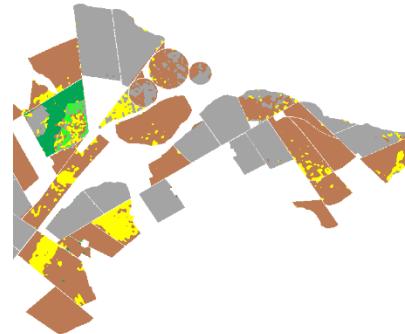
d) RF - AST



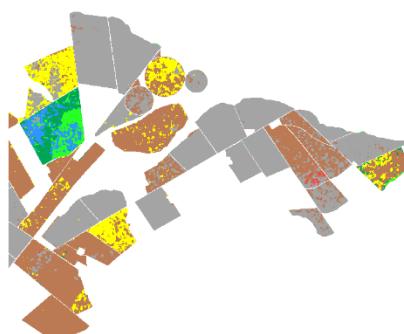
e) CNN - A



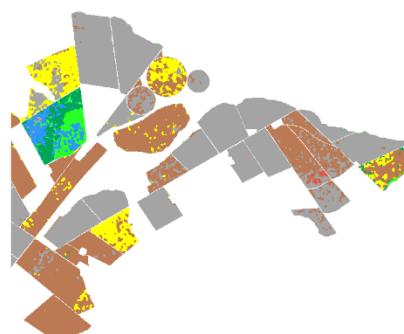
f) CNN - AS



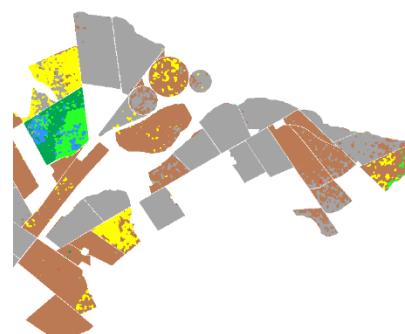
g) CNN - AST



h) CNN_{Stack} - A



i) CNN_{Stack} - AS



j) CNN_{Stack} - AST

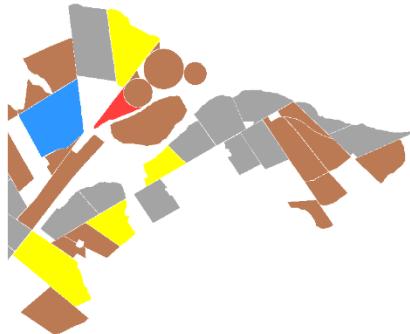
Resultados 1 sensor

Classification Maps

Sequence length: 14

Date: July 31st

Sensor: SAR



a) Reference

Classes:

Soybean

Pasture

Maize

Eucalyptus

Cotton

Soil

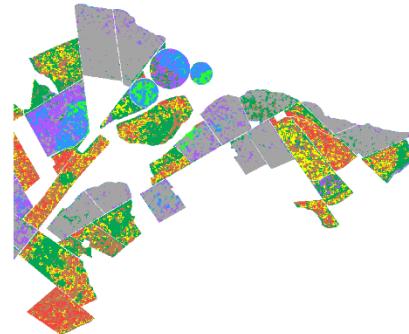
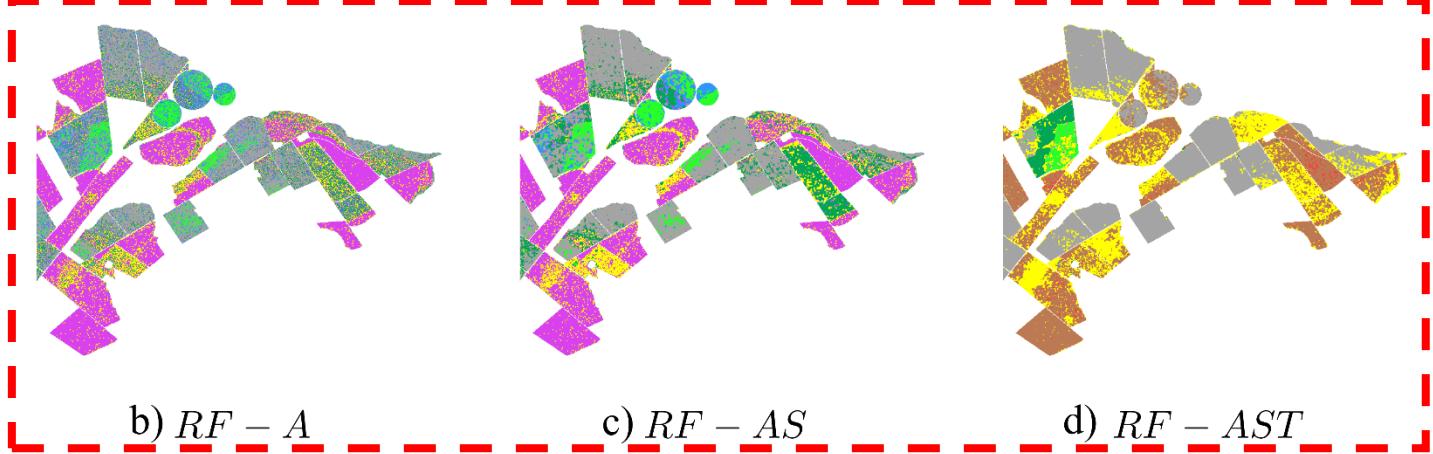
Sorghum

Turf grass

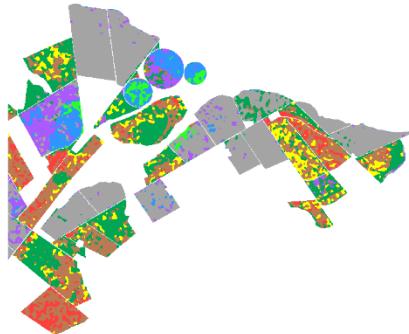
Beans

Cerrado

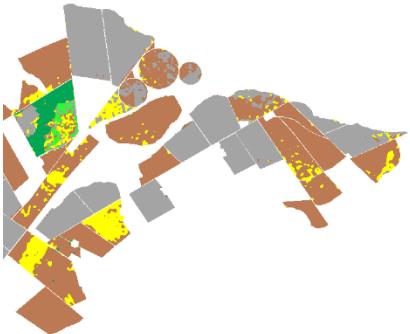
NCC



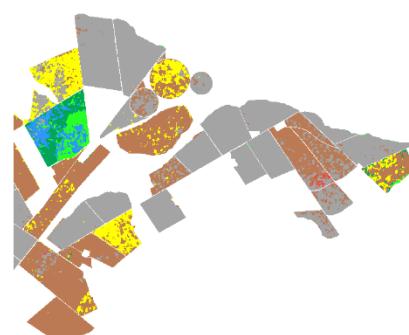
e) $CNN - A$



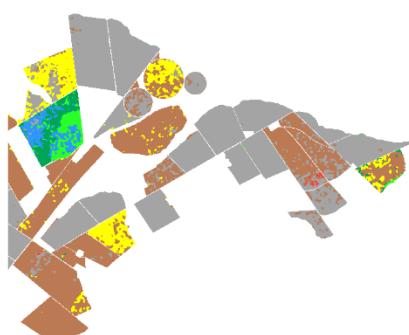
f) $CNN - AS$



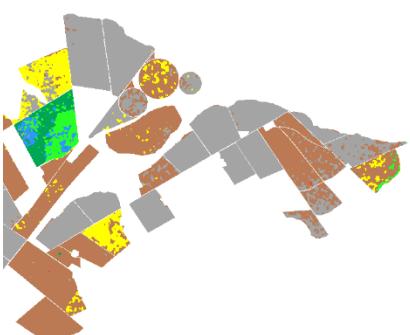
g) $CNN - AST$



h) $CNN_{Stack} - A$



i) $CNN_{Stack} - AS$



j) $CNN_{Stack} - AST$

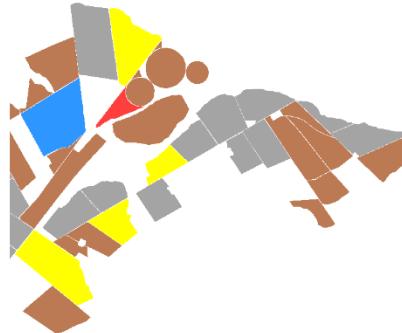
Resultados 1 sensor

Classification Maps

Sequence length: 14

Date: July 31st

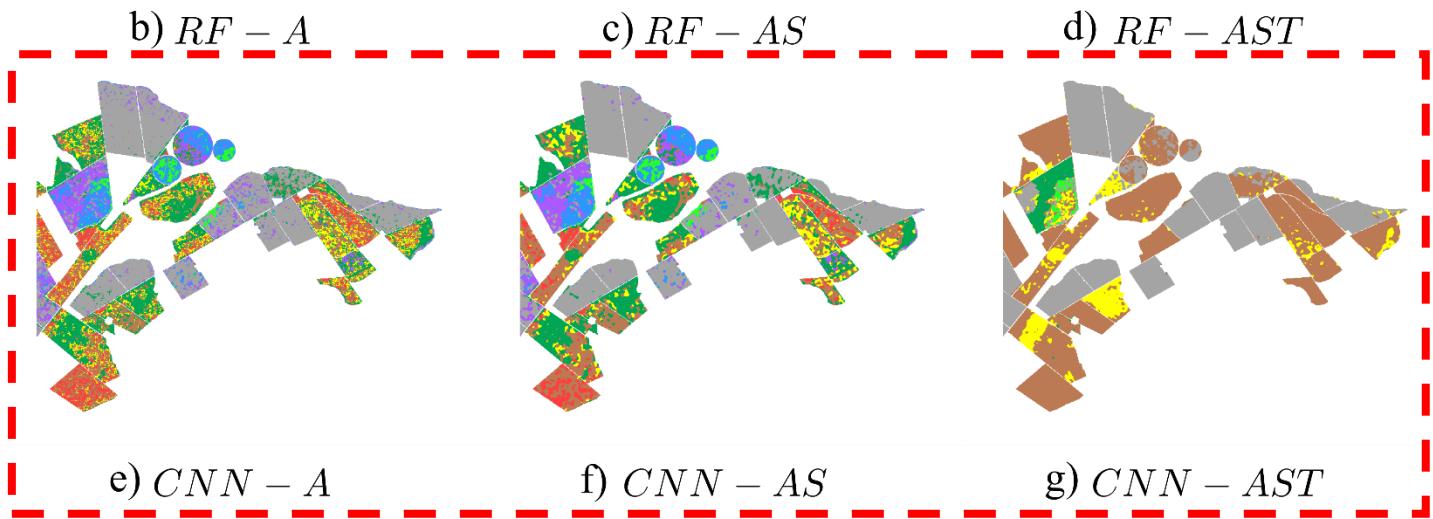
Sensor: SAR



a) Reference

Classes:

Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



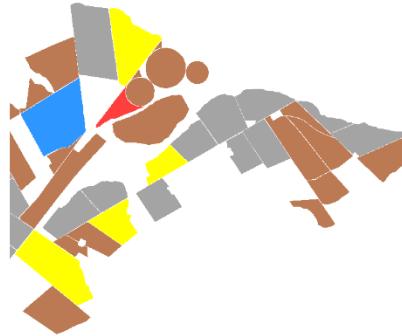
Resultados 1 sensor

Classification Maps

Sequence length: 14

Date: July 31st

Sensor: SAR



a) Reference

Classes:

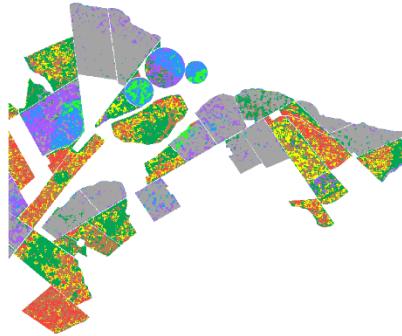
Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



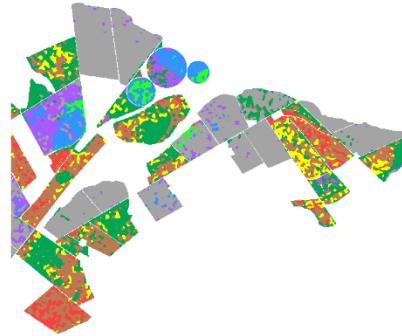
b) RF - A

c) RF - AS

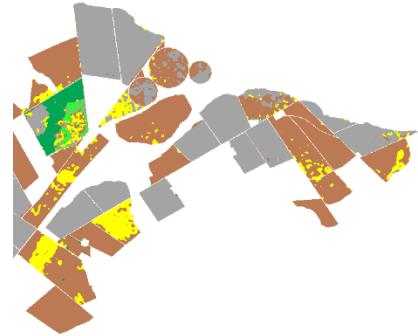
d) RF - AST



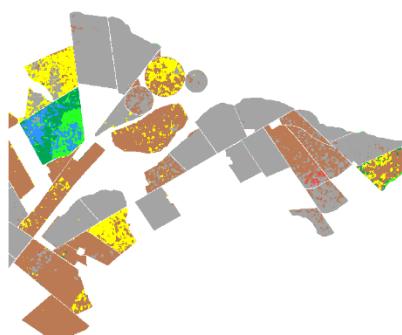
e) CNN - A



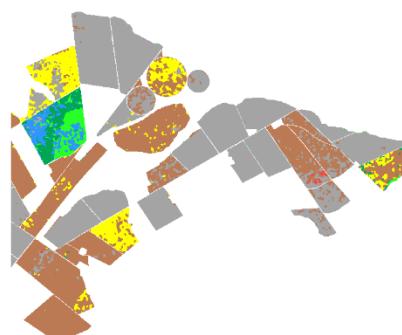
f) CNN - AS



g) CNN - AST



h) CNN_{Stack} - A



i) CNN_{Stack} - AS



j) CNN_{Stack} - AST

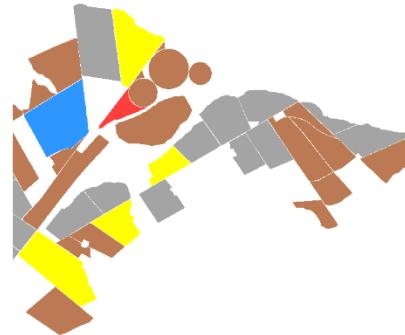
Resultados 1 sensor

Classification Maps

Sequence length: 14

Date: July 31st

Sensor: SAR

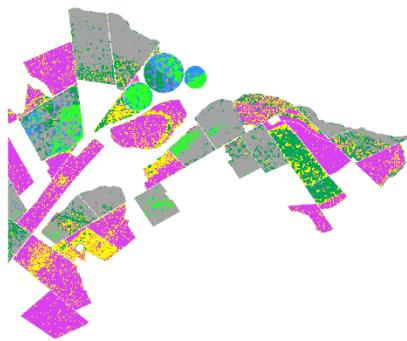


a) Reference

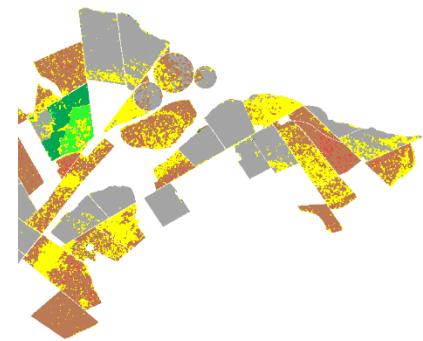
Classes:	
Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



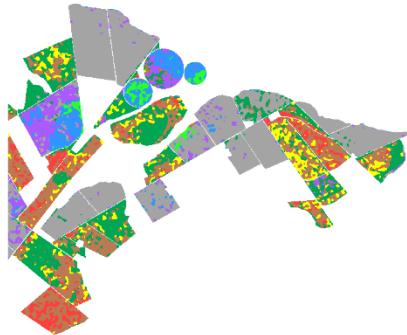
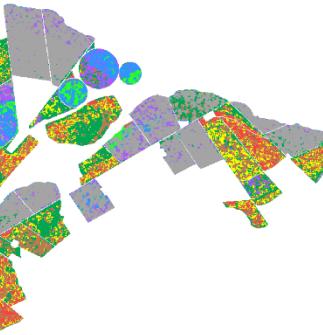
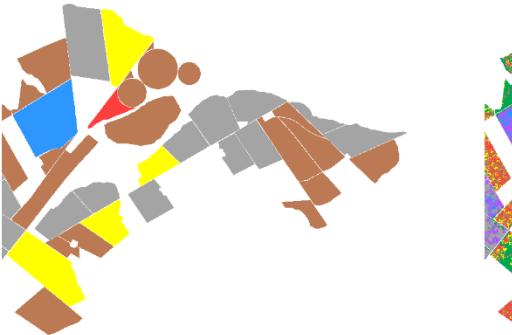
b) $RF - A$



c) $RF - AS$



d) $RF - AST$

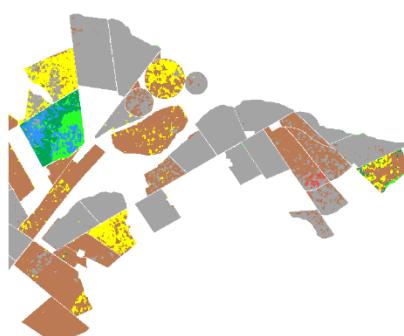


a) Reference

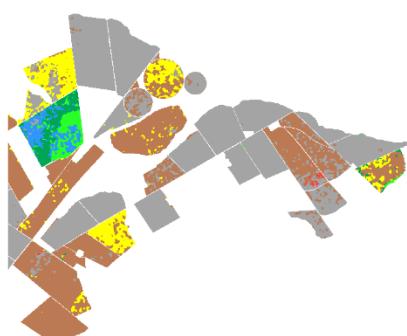
e) $CNN - A$

f) $CNN - AS$

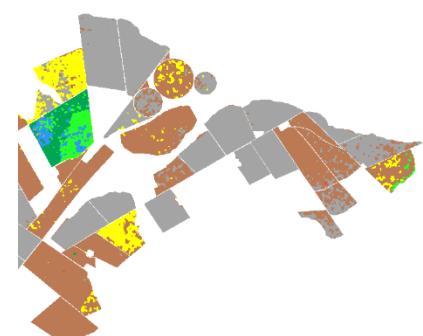
g) $CNN - AST$



h) $CNN_{Stack} - A$



i) $CNN_{Stack} - AS$



j) $CNN_{Stack} - AST$

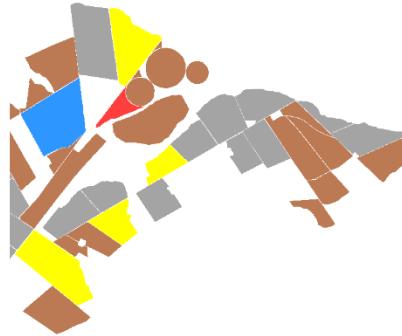
Resultados 1 sensor

Classification Maps

Sequence length: 14

Date: July 31st

Sensor: SAR

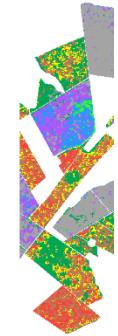
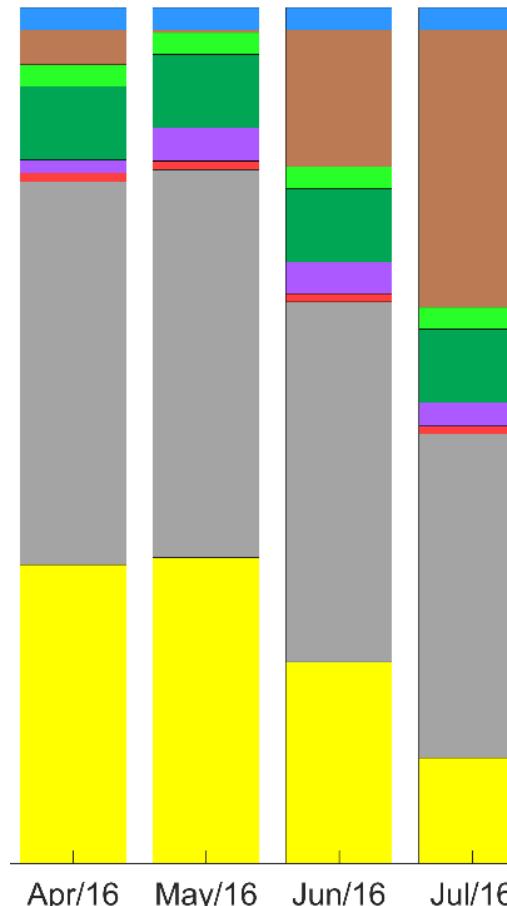


a) Reference

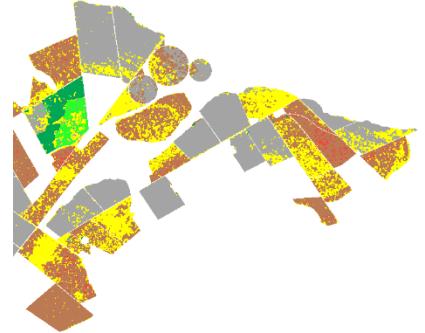
Classes:	
Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



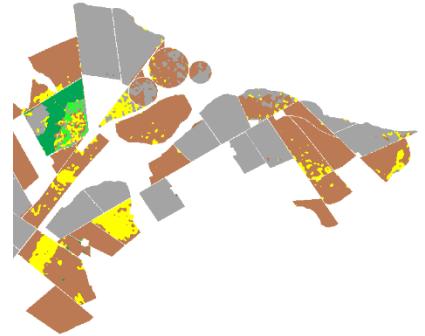
e



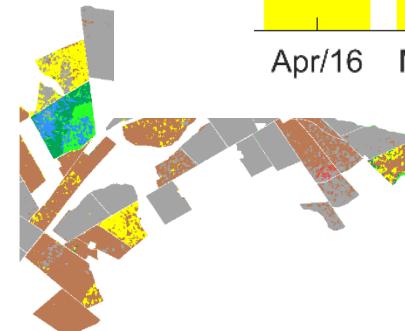
e



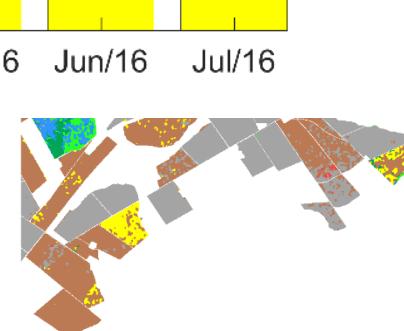
d) RF – AST



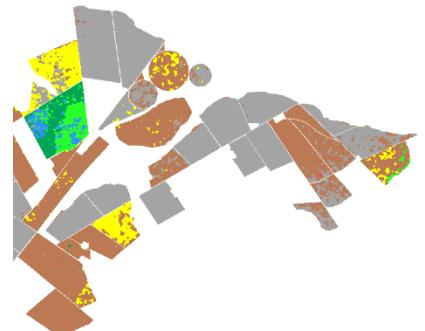
g) CNN – AST



h) $CNN_{Stack} - A$



i) $CNN_{Stack} - AS$



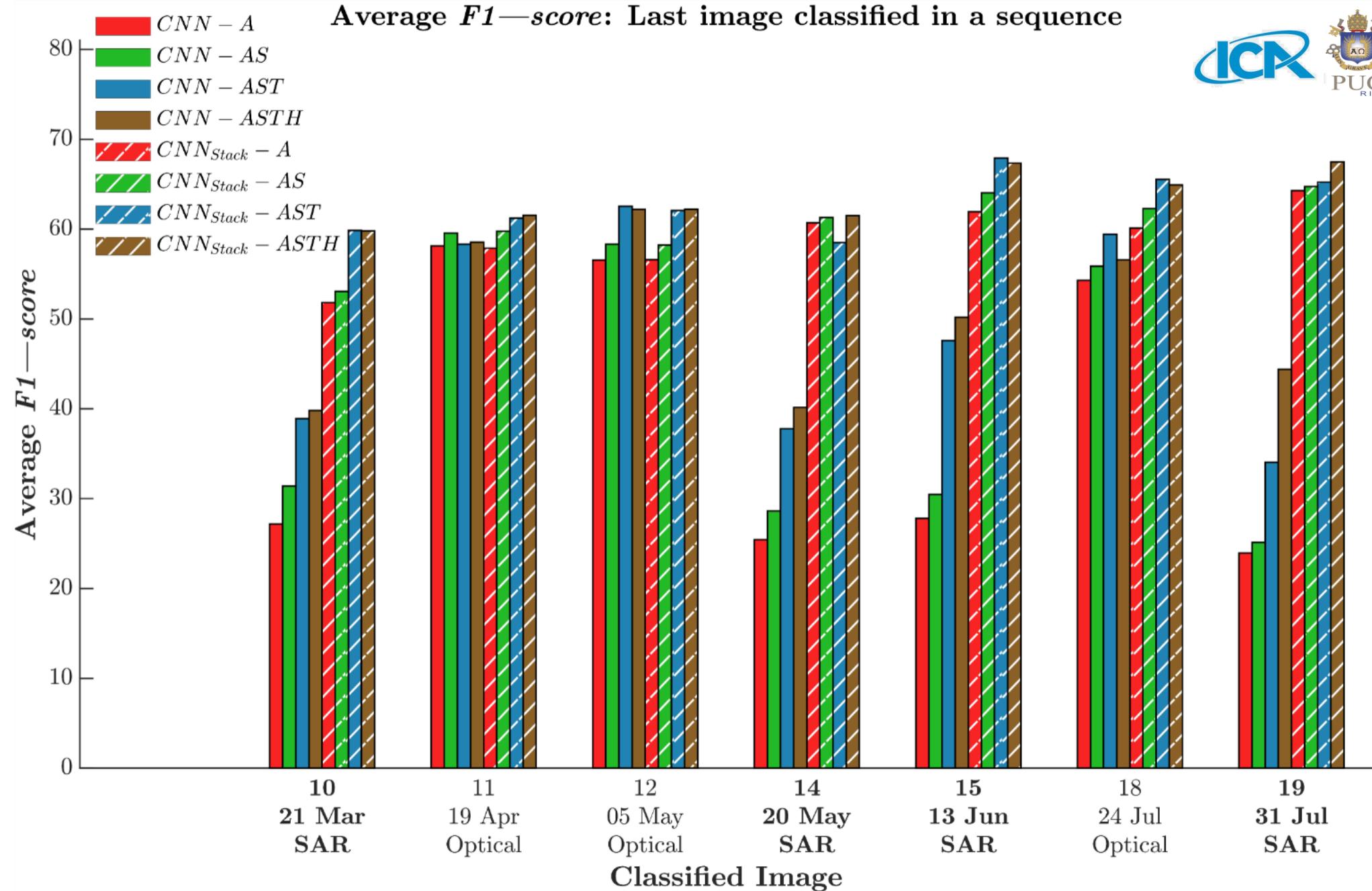
j) $CNN_{Stack} - AST$

Resultados Múltiples sensores

Resultados

Múltiples sensores

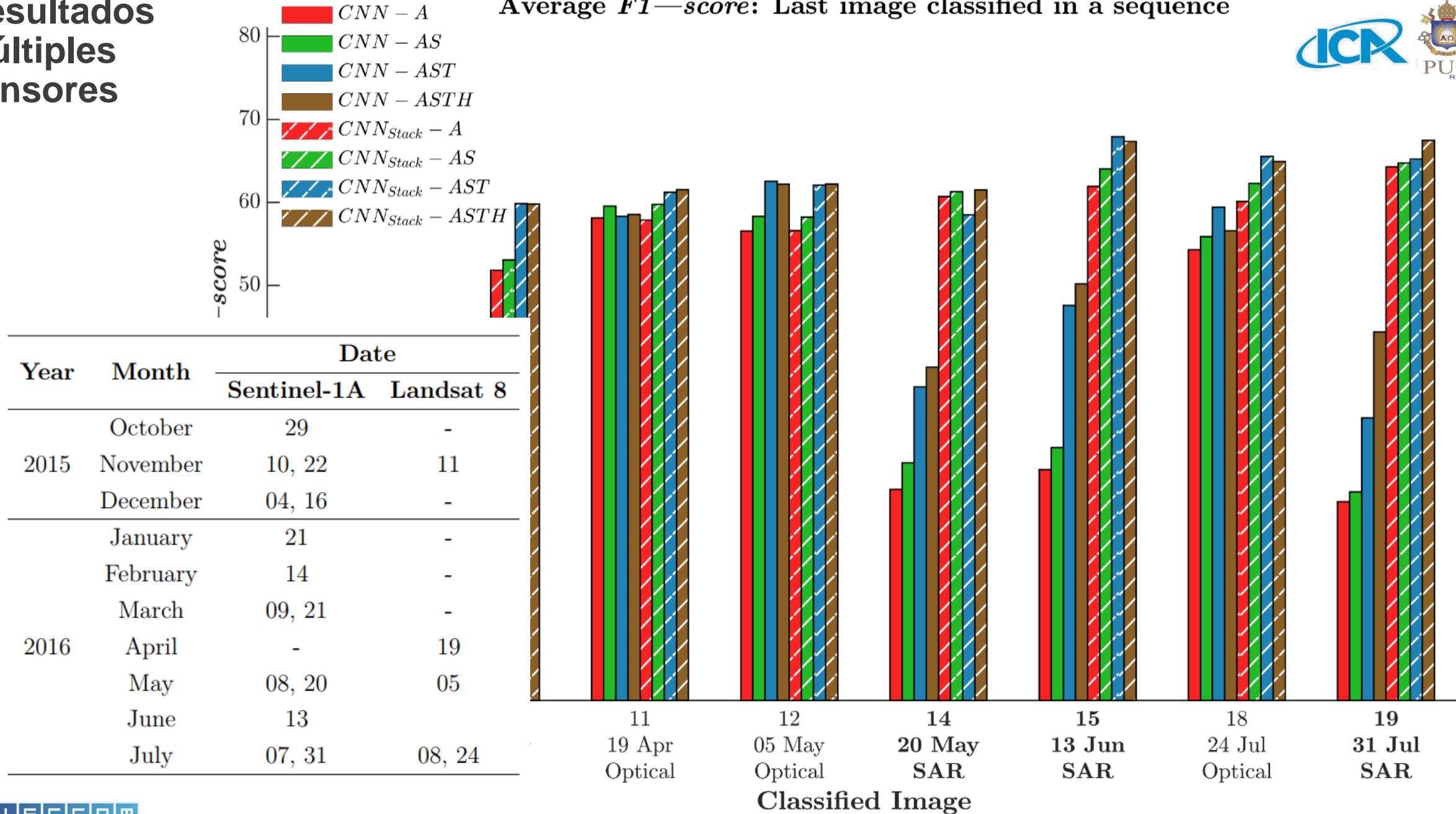
Average *F1-score*: Last image classified in a sequence



Resultados

Múltiples sensores

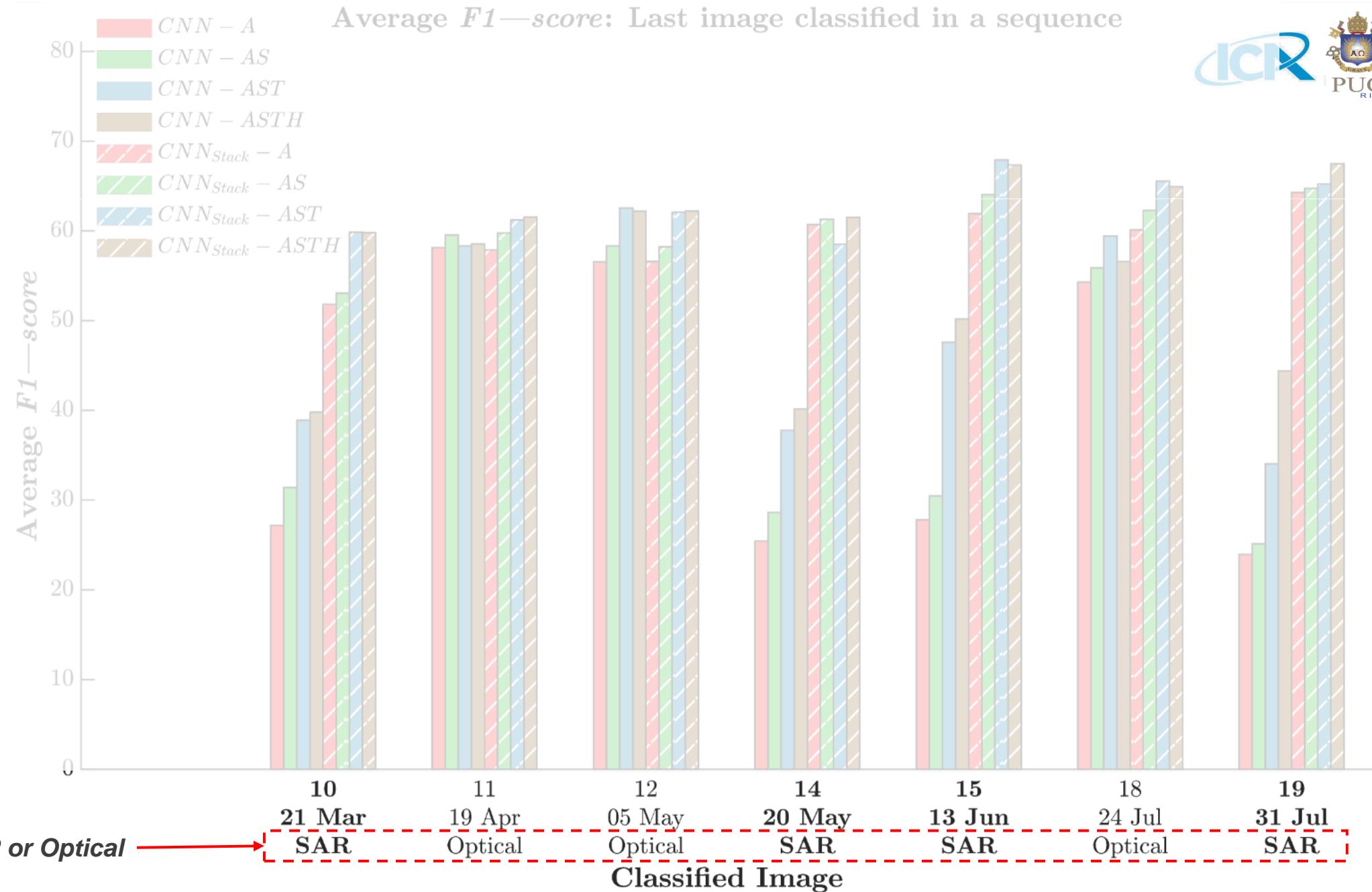
Average *F1-score*: Last image classified in a sequence



Resultados

Múltiples sensores

Average $F1$ —score: Last image classified in a sequence



Type of Image: SAR or Optical

21 Mar

SAR

19 Apr

Optical

05 May

Optical

20 May

SAR

13 Jun

SAR

24 Jul

Optical

31 Jul

SAR

Classified Image

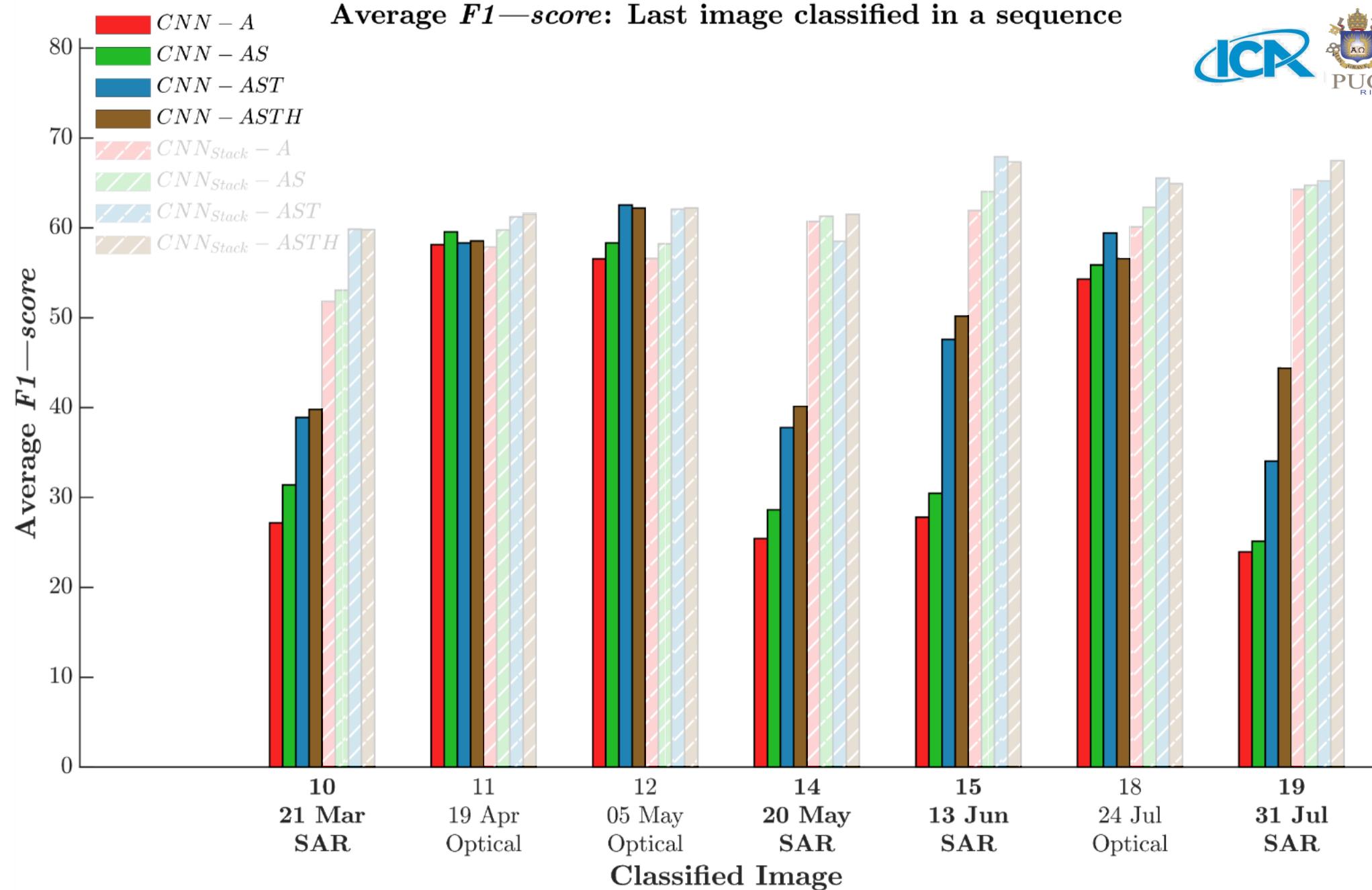
Pedro M. Achancaray Diaz

Resultados

Múltiples sensores

CNN single image

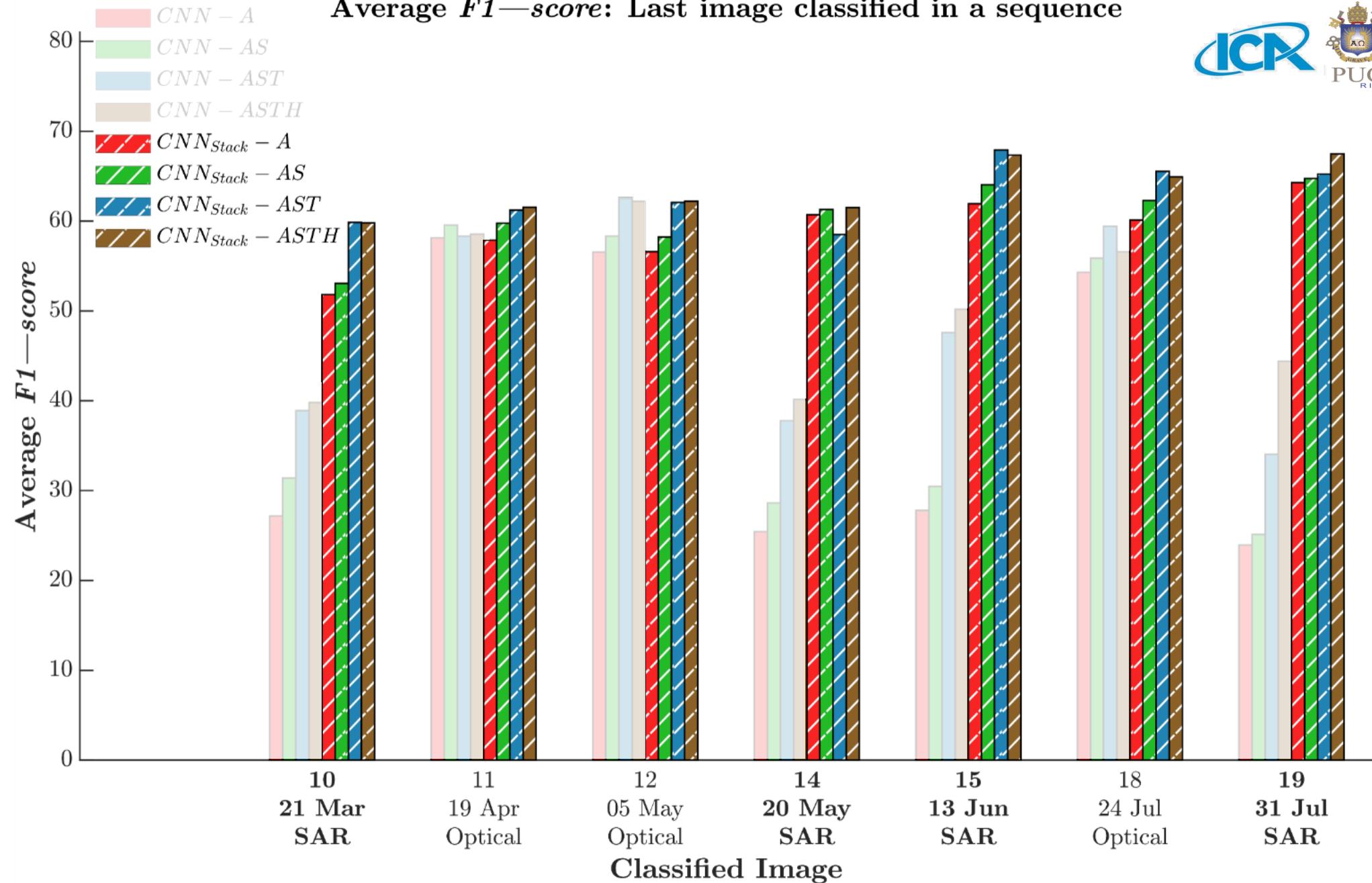
Average $F1$ —score: Last image classified in a sequence



Resultados Múltiples sensores

CNN image stack

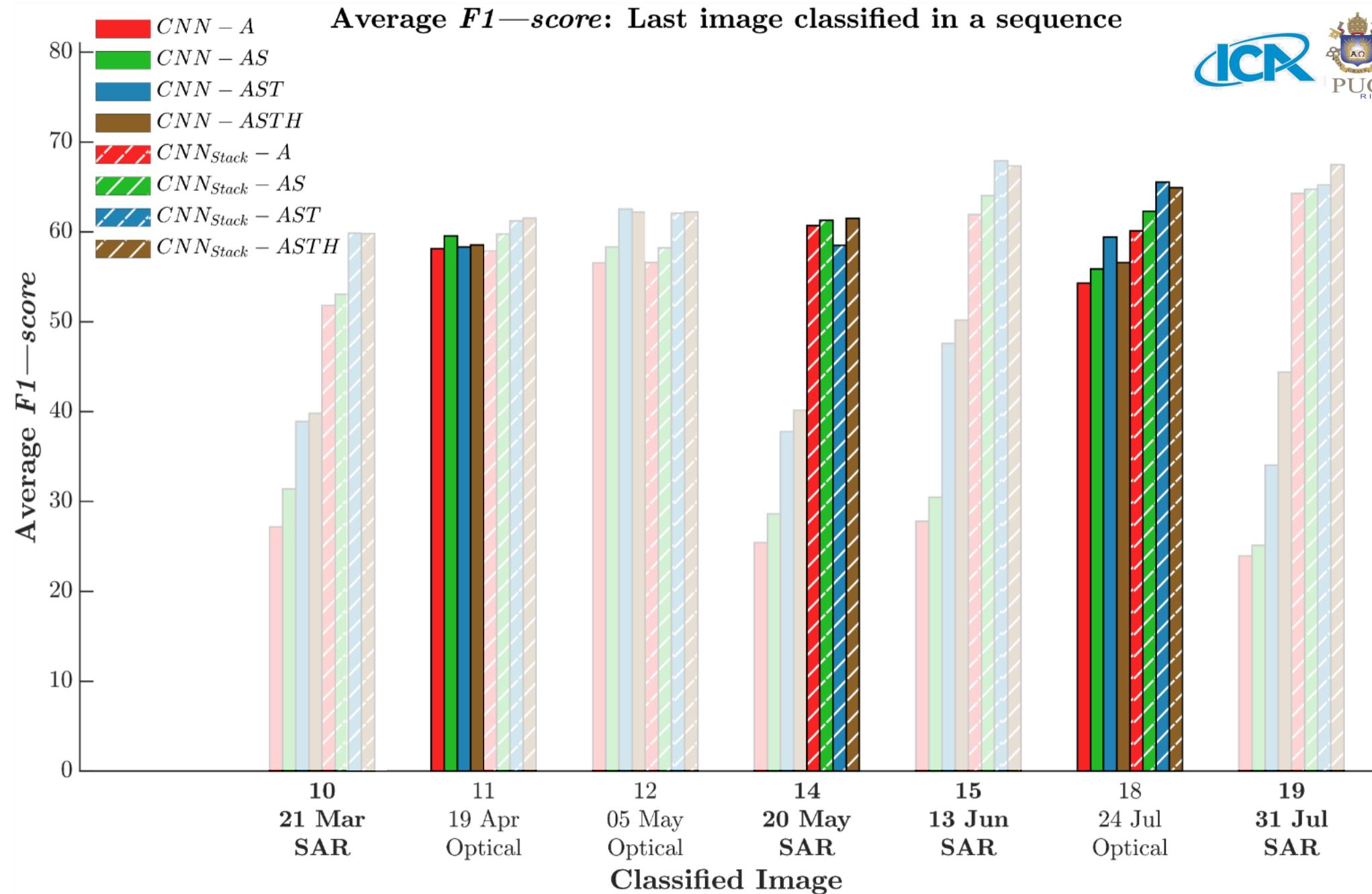
Average $F1$ —score: Last image classified in a sequence



Resultados Múltiples sensores

Epochs 11, 14 and 18

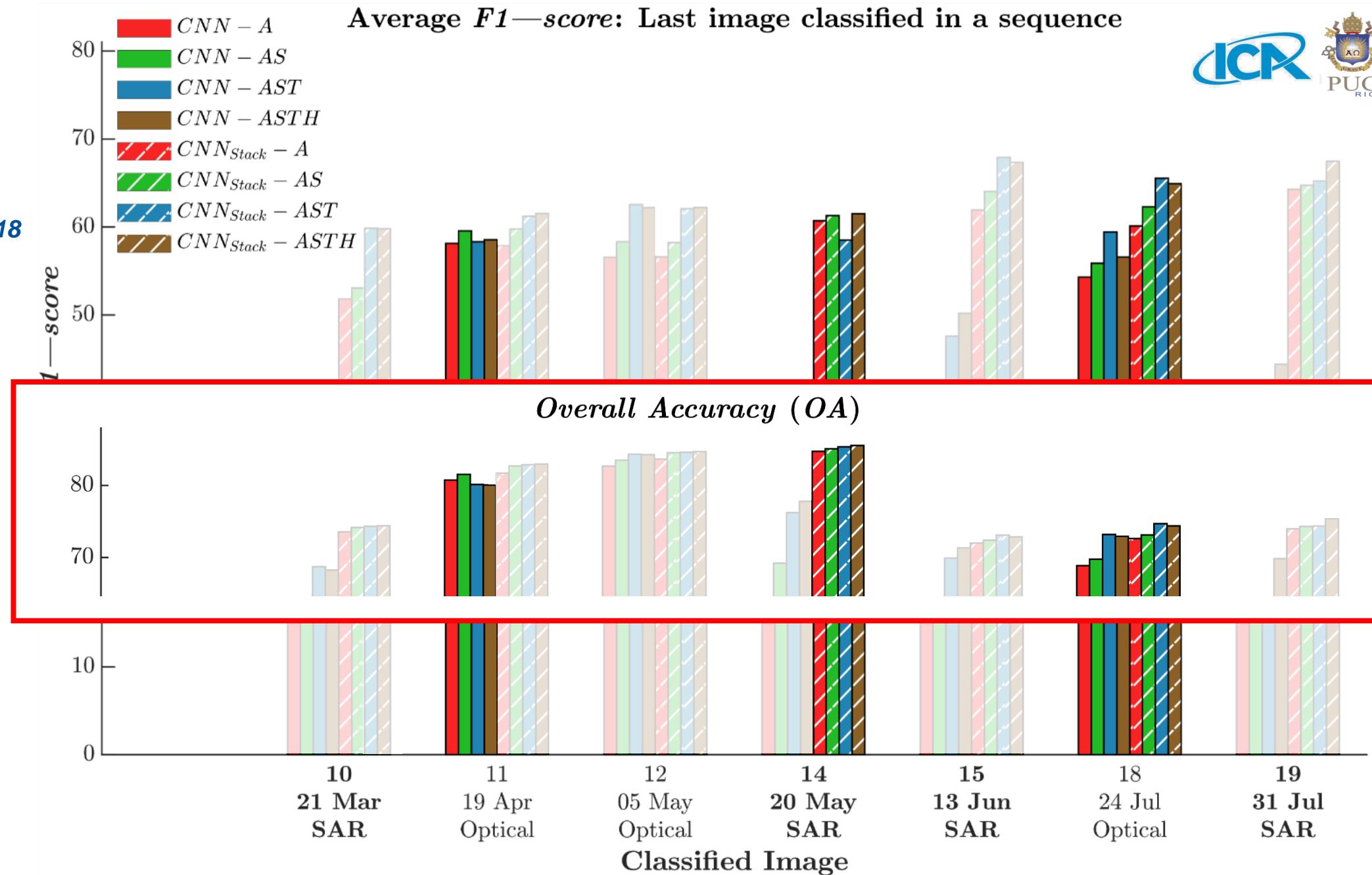
Average $F1$ —score: Last image classified in a sequence



Resultados Múltiples sensores

Epochs 11, 14 and 18

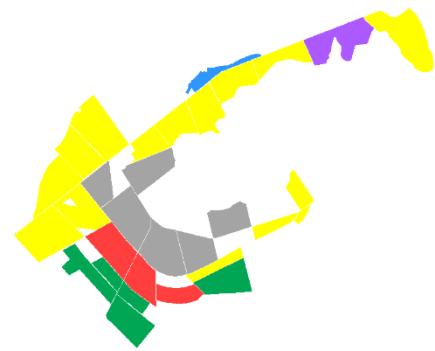
Average *F1-score*: Last image classified in a sequence



Resultados Múltiples sensores

Classification Maps

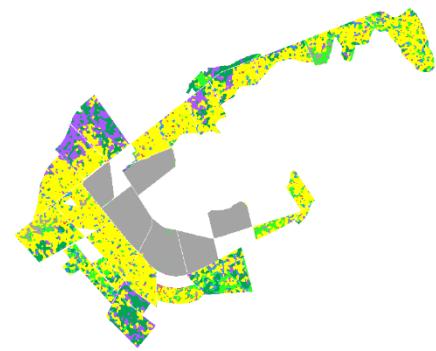
Sequence length: 14
Date: May 20th
Sensor: SAR



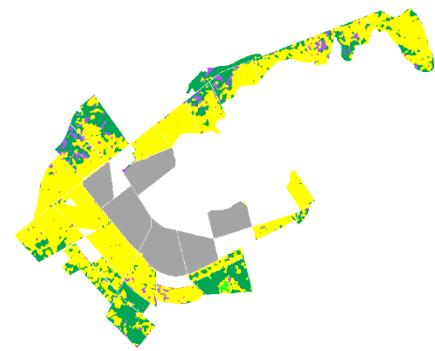
a) Reference



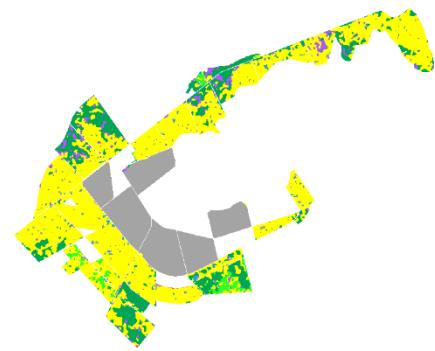
b) $CNN - A$



d) $CNN - AS$



f) $CNN - AST$



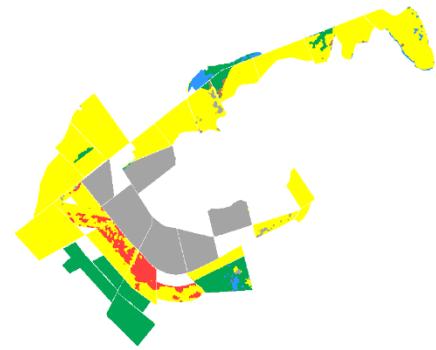
h) $CNN - ASTH$

Classes:

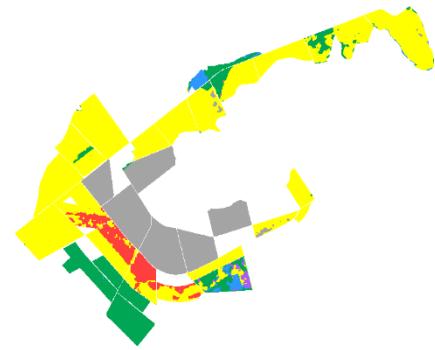
Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



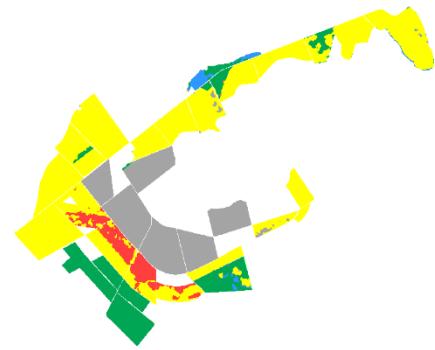
c) $CNN_{Stack} - A$



e) $CNN_{Stack} - AS$



g) $CNN_{Stack} - AST$

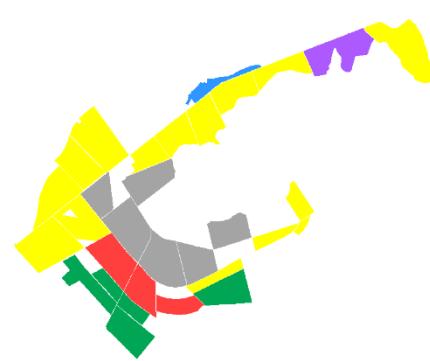


i) $CNN_{Stack} - ASTH$

Resultados Múltiples sensores

Classification Maps

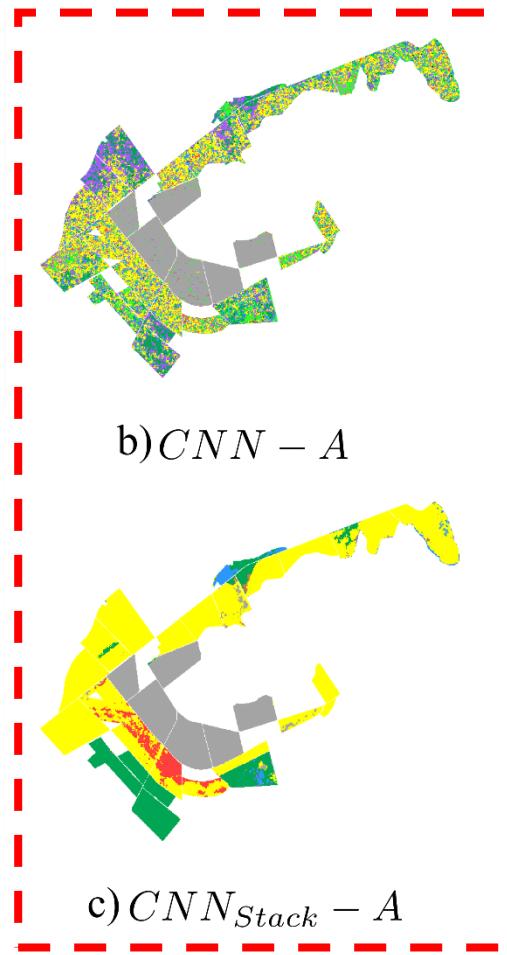
Sequence length: 14
Date: May 20th
Sensor: SAR



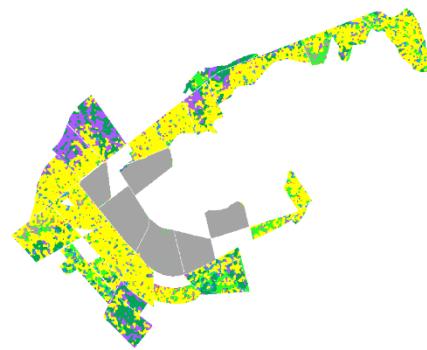
a) Reference

Classes:

Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



b) $CNN - A$



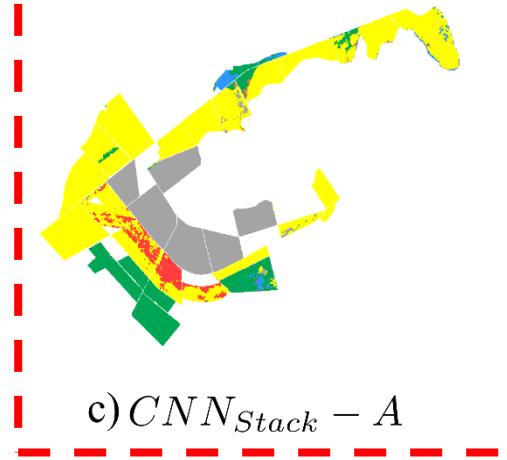
d) $CNN - AS$



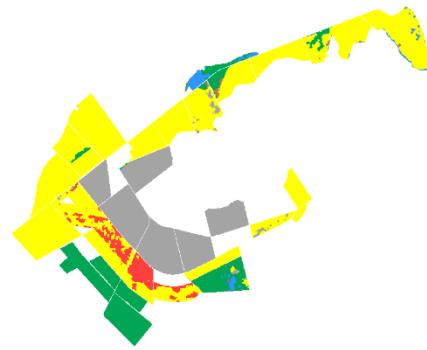
f) $CNN - AST$



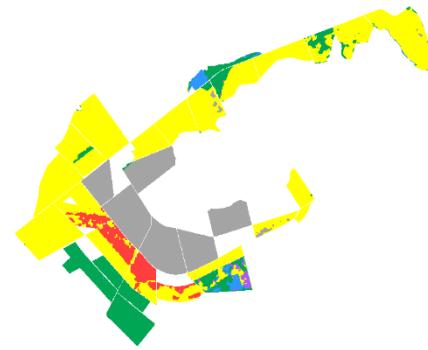
h) $CNN - ASTH$



c) $CNN_{Stack} - A$



e) $CNN_{Stack} - AS$



g) $CNN_{Stack} - AST$

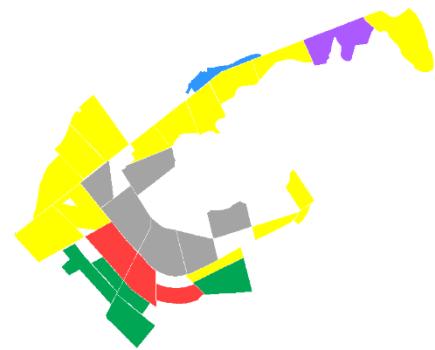


i) $CNN_{Stack} - ASTH$

Resultados Múltiples sensores

Classification Maps

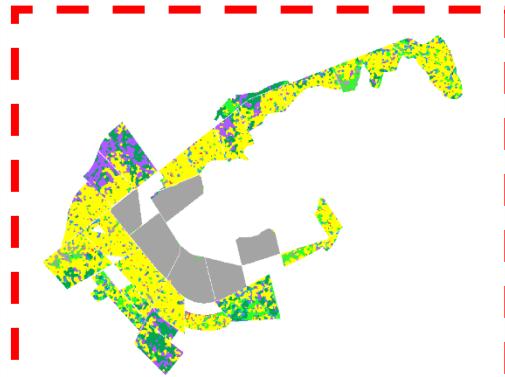
Sequence length: 14
Date: May 20th
Sensor: SAR



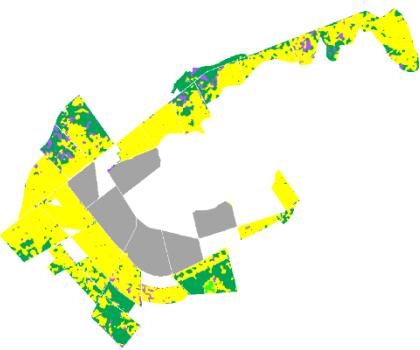
a) Reference



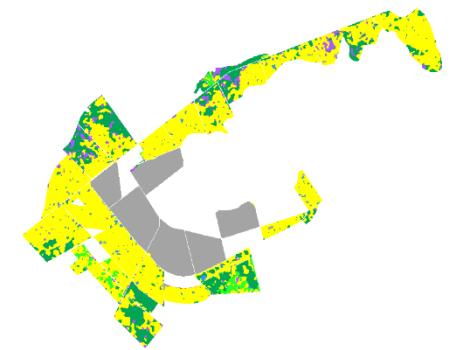
b) $CNN - A$



d) $CNN - AS$



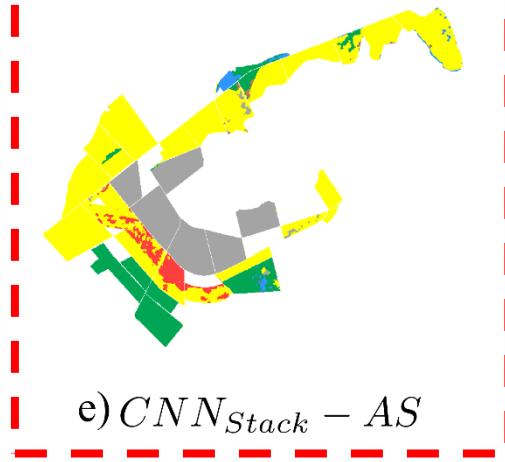
f) $CNN - AST$



h) $CNN - ASTH$



c) $CNN_{Stack} - A$



e) $CNN_{Stack} - AS$



g) $CNN_{Stack} - AST$



i) $CNN_{Stack} - ASTH$

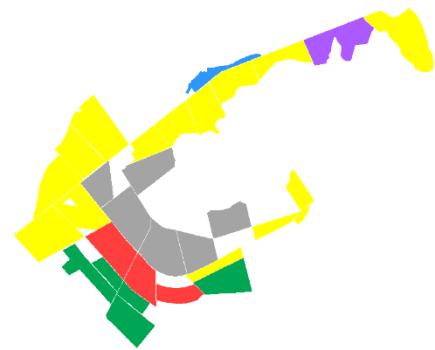
Classes:

Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	

Resultados Múltiples sensores

Classification Maps

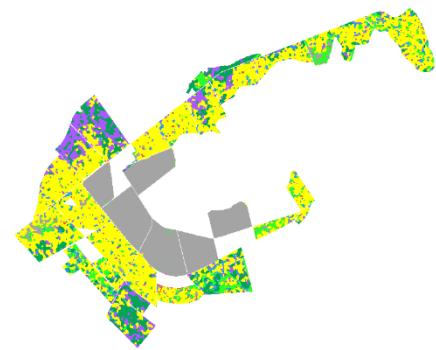
Sequence length: 14
Date: May 20th
Sensor: SAR



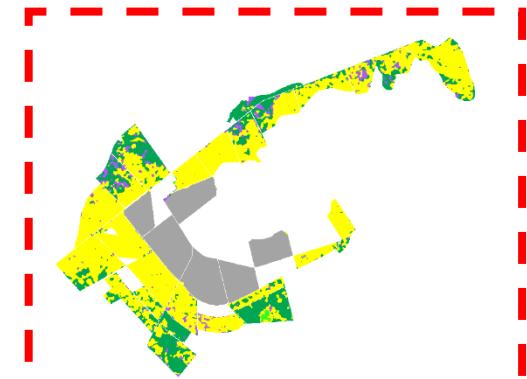
a) Reference



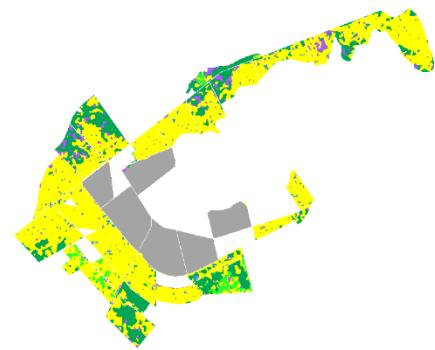
b) $CNN - A$



d) $CNN - AS$



f) $CNN - AST$



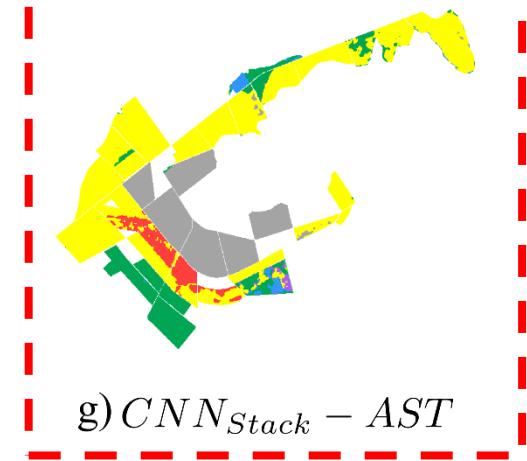
h) $CNN - ASTH$



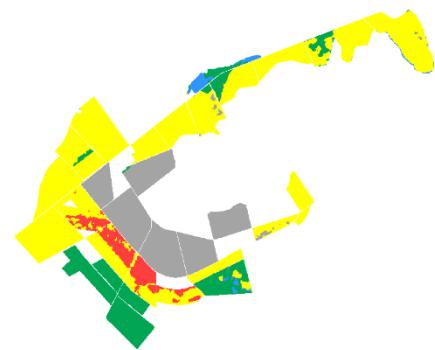
c) $CNN_{Stack} - A$



e) $CNN_{Stack} - AS$



g) $CNN_{Stack} - AST$



i) $CNN_{Stack} - ASTH$

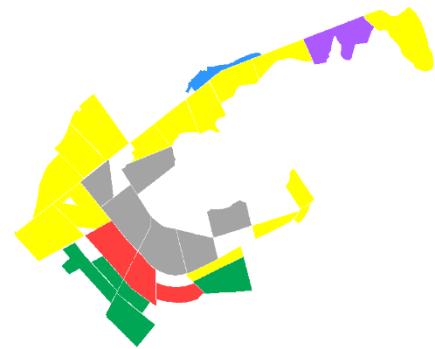
Classes:

Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	

Resultados Múltiples sensores

Classification Maps

Sequence length: 14
Date: May 20th
Sensor: SAR



a) Reference



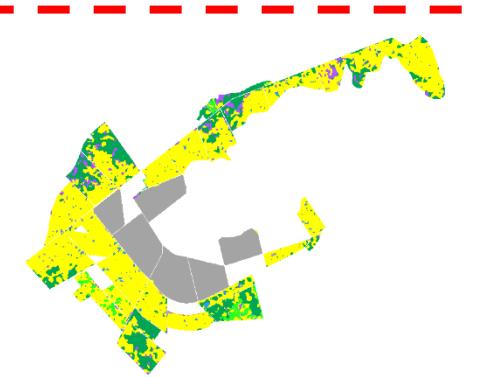
b) $CNN - A$



d) $CNN - AS$



f) $CNN - AST$



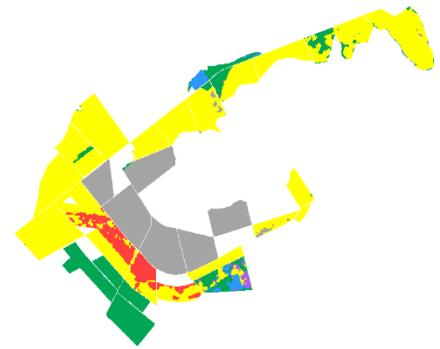
h) $CNN - ASTH$



c) $CNN_{Stack} - A$



e) $CNN_{Stack} - AS$



g) $CNN_{Stack} - AST$



i) $CNN_{Stack} - ASTH$

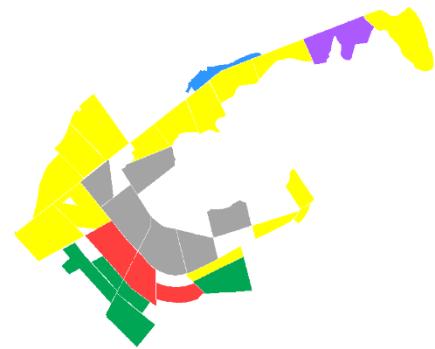
Classes:

Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	

Resultados Múltiples sensores

Classification Maps

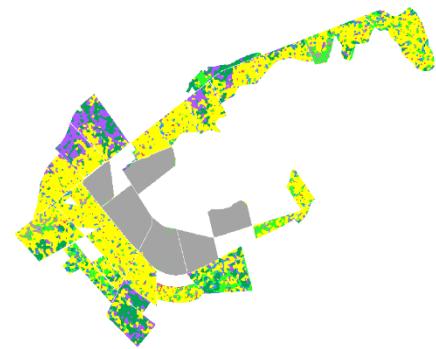
Sequence length: 14
Date: May 20th
Sensor: SAR



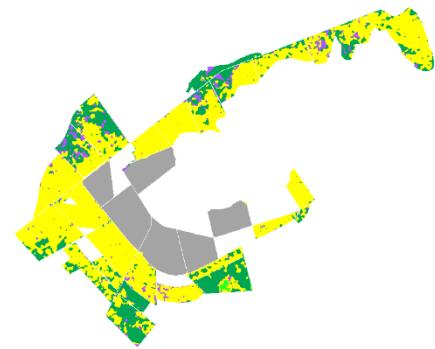
a) Reference



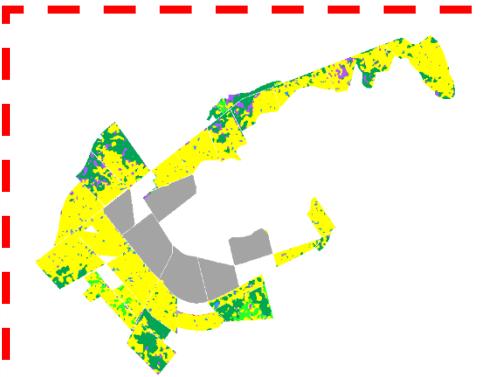
b) $CNN - A$



d) $CNN - AS$



f) $CNN - AST$



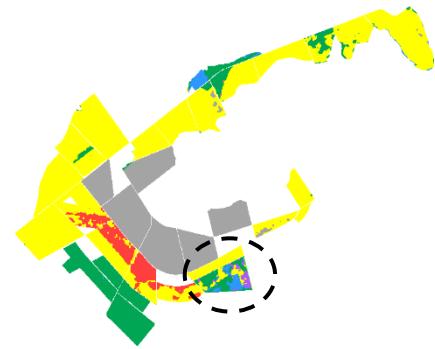
h) $CNN - ASTH$



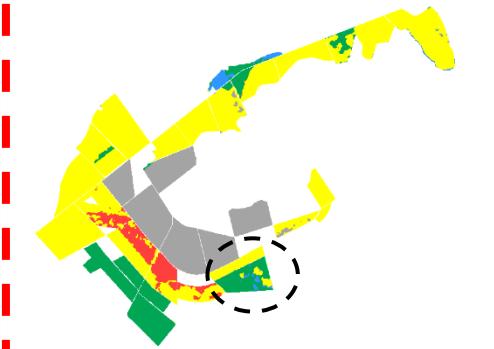
c) $CNN_{Stack} - A$



e) $CNN_{Stack} - AS$



g) $CNN_{Stack} - AST$



i) $CNN_{Stack} - ASTH$

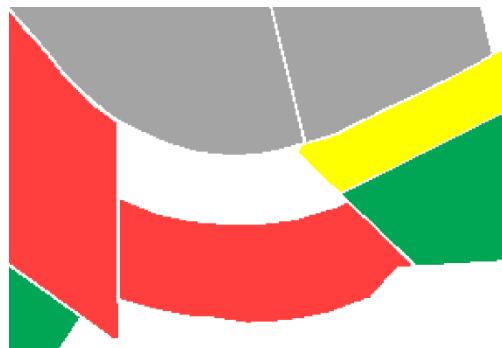
Classes:

Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	

Resultados Múltiples sensores

Classification Maps

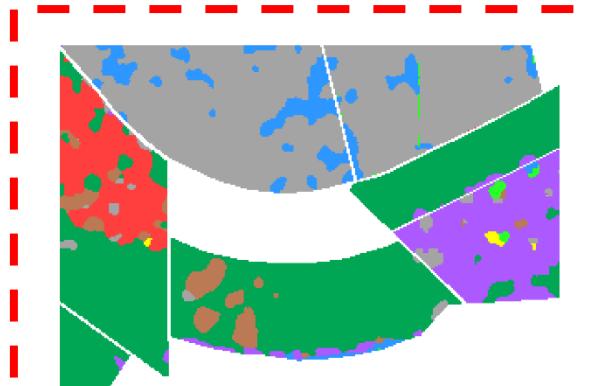
Sequence length: 19
Date: July 31st
Sensor: SAR



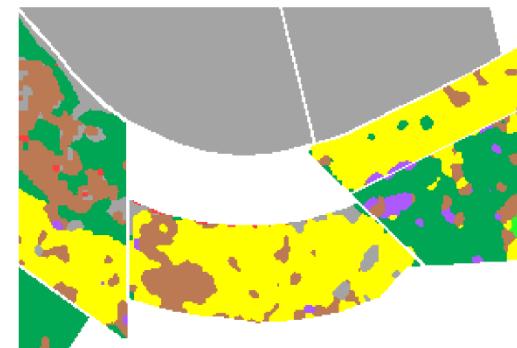
a) Reference

Classes:

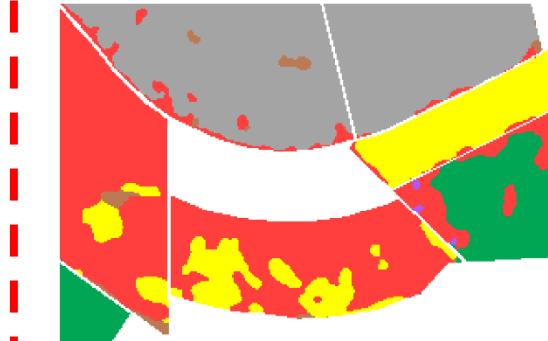
Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



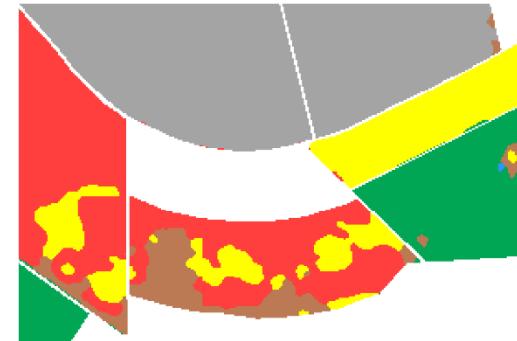
b) $CNN - AST$



c) $CNN - ASTH$



d) $CNN_{Stack} - AST$

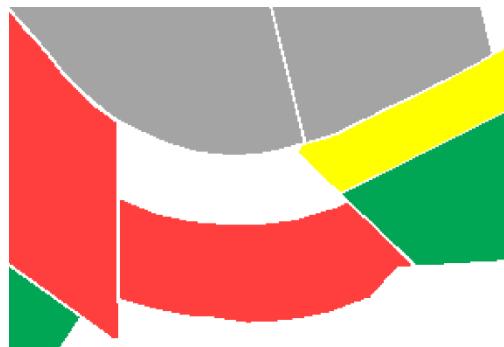


e) $CNN_{Stack} - ASTH$

Resultados Múltiples sensores

Classification Maps

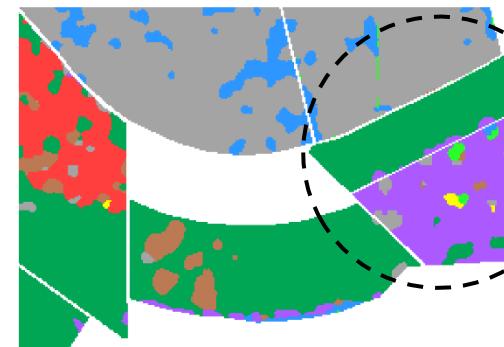
Sequence length: 19
Date: July 31st
Sensor: SAR



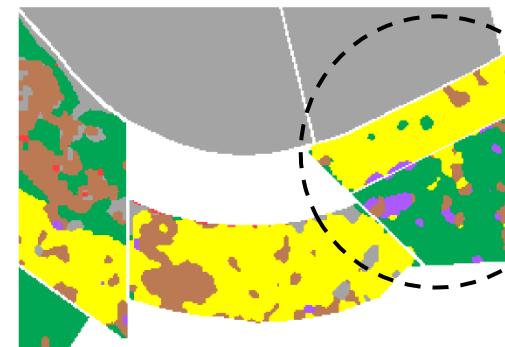
a) Reference

Classes:

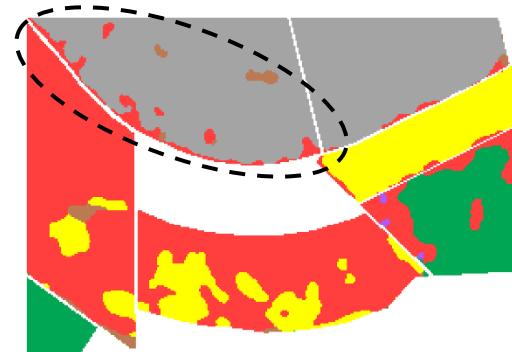
Soybean	Pasture
Maize	Eucalyptus
Cotton	Soil
Sorghum	Turf grass
Beans	Cerrado
NCC	



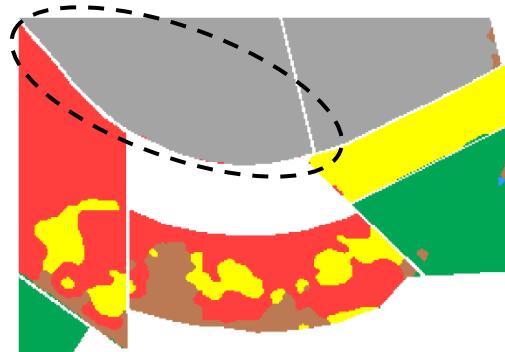
b) CNN – AST



c) CNN – ASTH



d) CNN_{Stack} – AST



e) CNN_{Stack} – ASTH

Outline

1. Introducción

2. CRFs

3. Resultados

4. Conclusiones

Conclusiones

- Campo Verde: **85% Overall Accuracy** y **68% average F1-score**.
- Variantes basadas en CNN (**single image** y **image stack**) obtuvieron mejores resultados que sus correspondientes usando **Random Forest** y **atributos de textura (GLCM)**.
- Cada **potencial** del CRF adicionó mayor información de contexto: **espacial** y **temporal**, mejorando la clasificación
- La adición de conexiones de mayor orden ayudó a corregir algunas parcelas que fueron erróneamente clasificadas.

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Reconocimiento de cultivos agrícolas en regiones tropicales usando secuencias de imágenes de teledetección de sensores activos y pasivos

Ph.D. Pedro M. Achancaray Diaz

pedro.diaz@puc-rio.br