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Image Classification Methods Assessment for Identification of Small-Scale Agriculture in Brazilian Amazon

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Flávia Domingos Pacheco

Bachelor's Degree in **Environmental Management** (Luiz de Queiroz School of Agriculture/ University of São Paulo, 2012-2017), with a period of studies at the University of Copenhagen/ Denmark (2015-2016), where I took Master's degree courses focused on **landscape transformation, ecological restoration, ethnobotany and conservation biology**.

After finishing my bachelor's degree, I worked as a **researcher of applied botany** (2018-2019) in a project of Urban forest management, funded by São Paulo Research Foundation.

I am currently a **Master's student in Remote Sensing** at the Brazilian National Institute for Space Research (2020-2022), her research is of land use and land cover changes in the Brazilian Amazon and I am member of the **Laboratory for investigation of Socioenvironmental Systems**.

Topics of research interest and current projects

Laboratory for investigation of
Socio-Environmental Systems

TREES
TRopical Ecosystems and Environmental Sciences lab

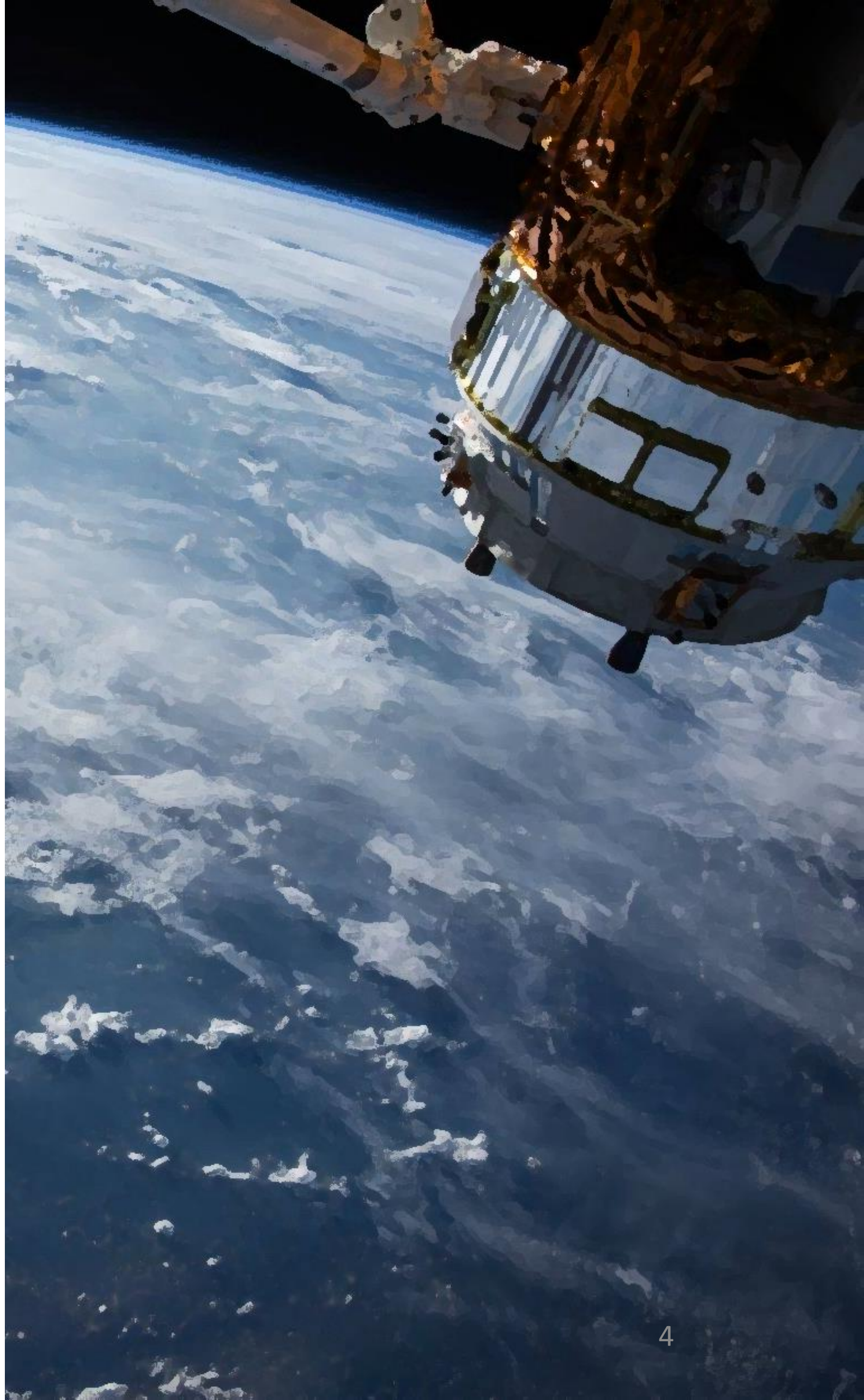
- Land Use Change in Amazon: Institutional Analysis and Modelling at multiple temporal and spatial scales;
- Scenarios for the Amazon: Climate, Biodiversity and Land use;
- Environmental Monitoring of the Amazon Biome by Satellite.

https://www.lissinpe.com.br/

- Assessment of forest deforestation impacts;
- Quantification of forest biomass and carbon stock;
- Remote sensing mapping of burnt forests.

http://www.treeslab.org/

1. Introduction
2. State of the art
3. Material and methods
4. Results and discussion
5. Conclusion



Small-scale agriculture

Food for local population

Income for families

Invisible

Cassava

Cassava

Black pepper

Papaya

Images from:

Laboratory for investigation of
Socio-Environmental Systems

This paper aims to test different methods for image classification focusing on small-scale agriculture in the region of Mocajuba and Cametá, municipalities in the Northeast of Pará state, Brazil

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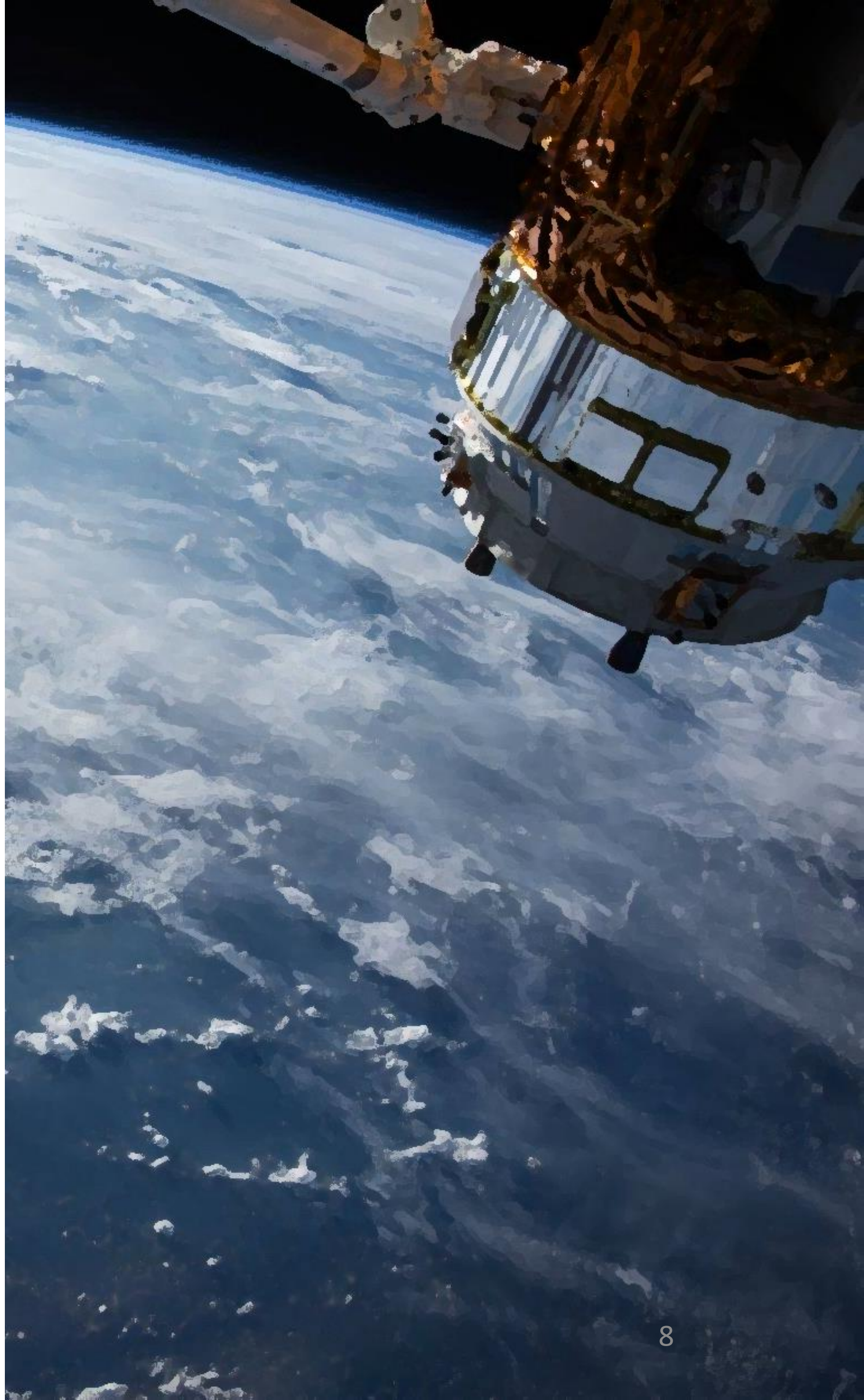

What can we find about small-scale agriculture mapping by using remote sensing techniques?

1

Remote sensing techniques

In Brazilian Amazon, several studies on agriculture have been carried out. Yet, most of them addresses large-scale agriculture

2

Small-scale agriculture

Few studies can be found. On the other hand, there are plenty of techniques that can be tested for mapping this land use class

3

Contribution

Testing and evaluating techniques capable of detecting this type of agriculture, which is largely invisible, despite its importance to society, environment and economy

We could observe the combination of different techniques: in some studies, authors adapted and tested techniques used to large-scale agriculture, but considering the unique features of small-scale agriculture in Amazon.

Maximum likelihood + neural networks	Multiresolution segmentation + adapted nearest neighbor	Segmentation + random forest

Object-based analysis are broadly used in many studies: segmentation allows the use of more features, such as shape, texture and so on, rather than only spectral ones. Small-scale agriculture has specific shape and texture, and spectral mixture, so an object-based analysis unfolds as a key technique.

Inoue et al. (2007), Blaschke (2010), Dutrieux et al. (2015), Vogels et al. (2019), Souza et al. (2019), Nguyen et al. (2020)

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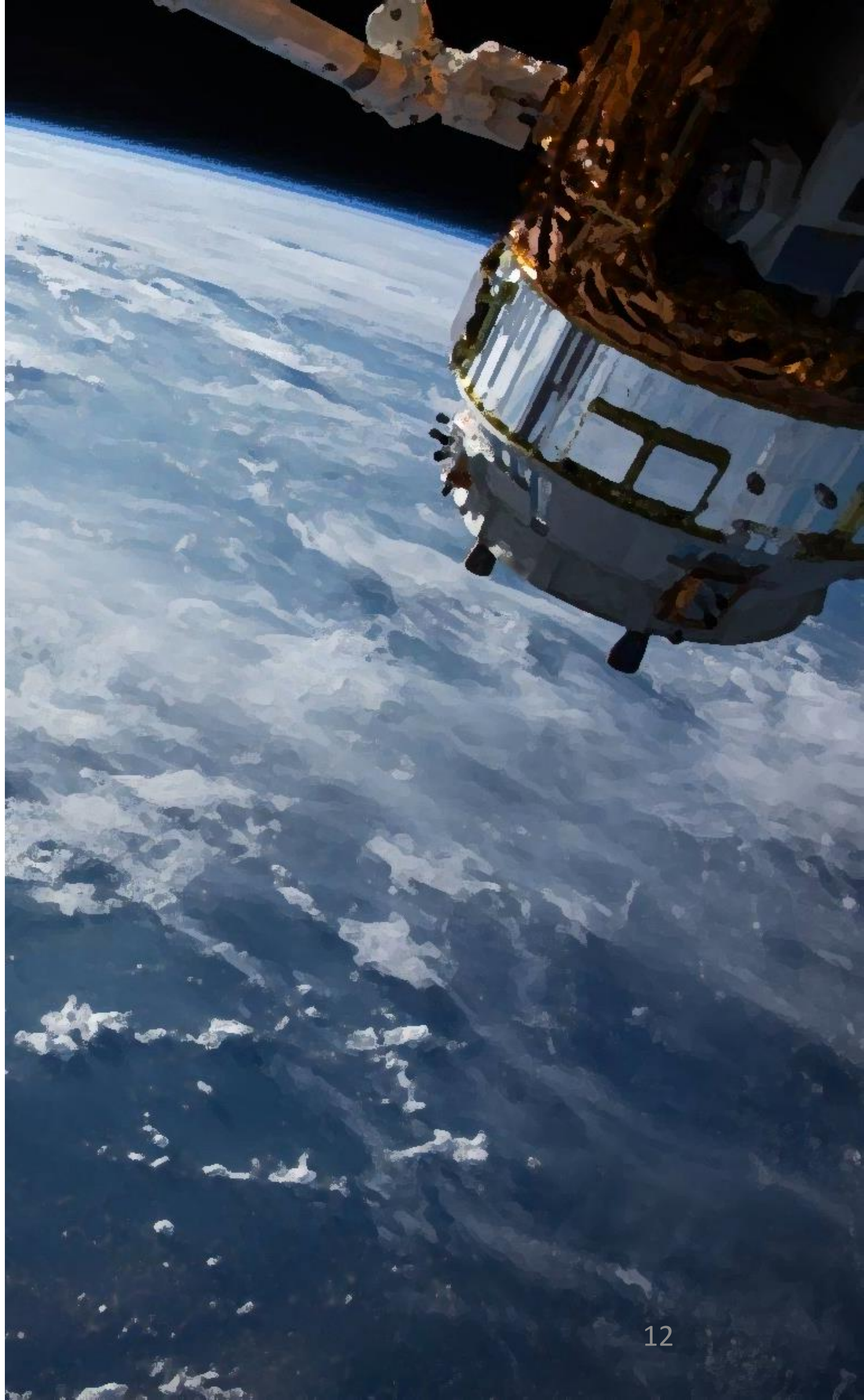
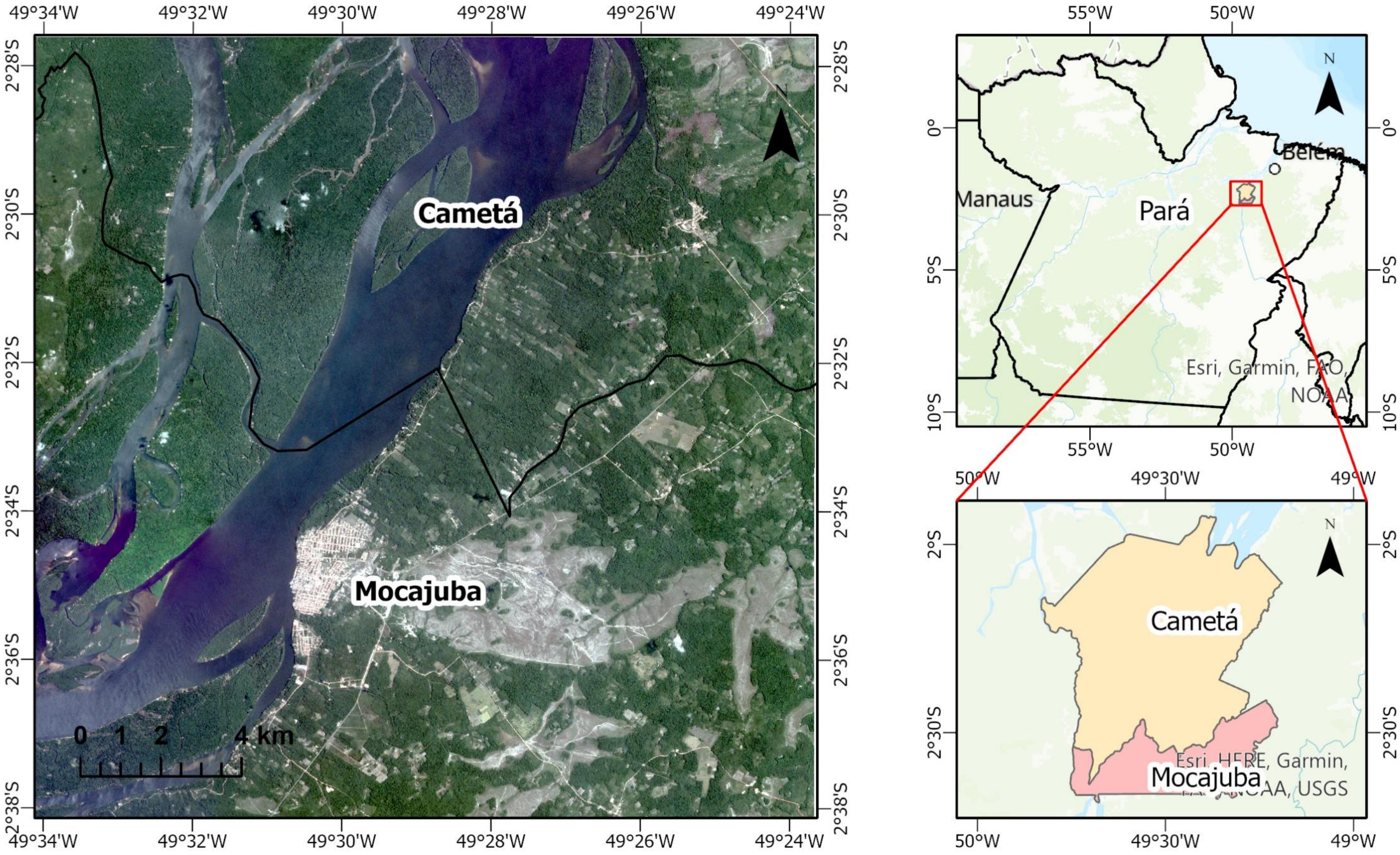


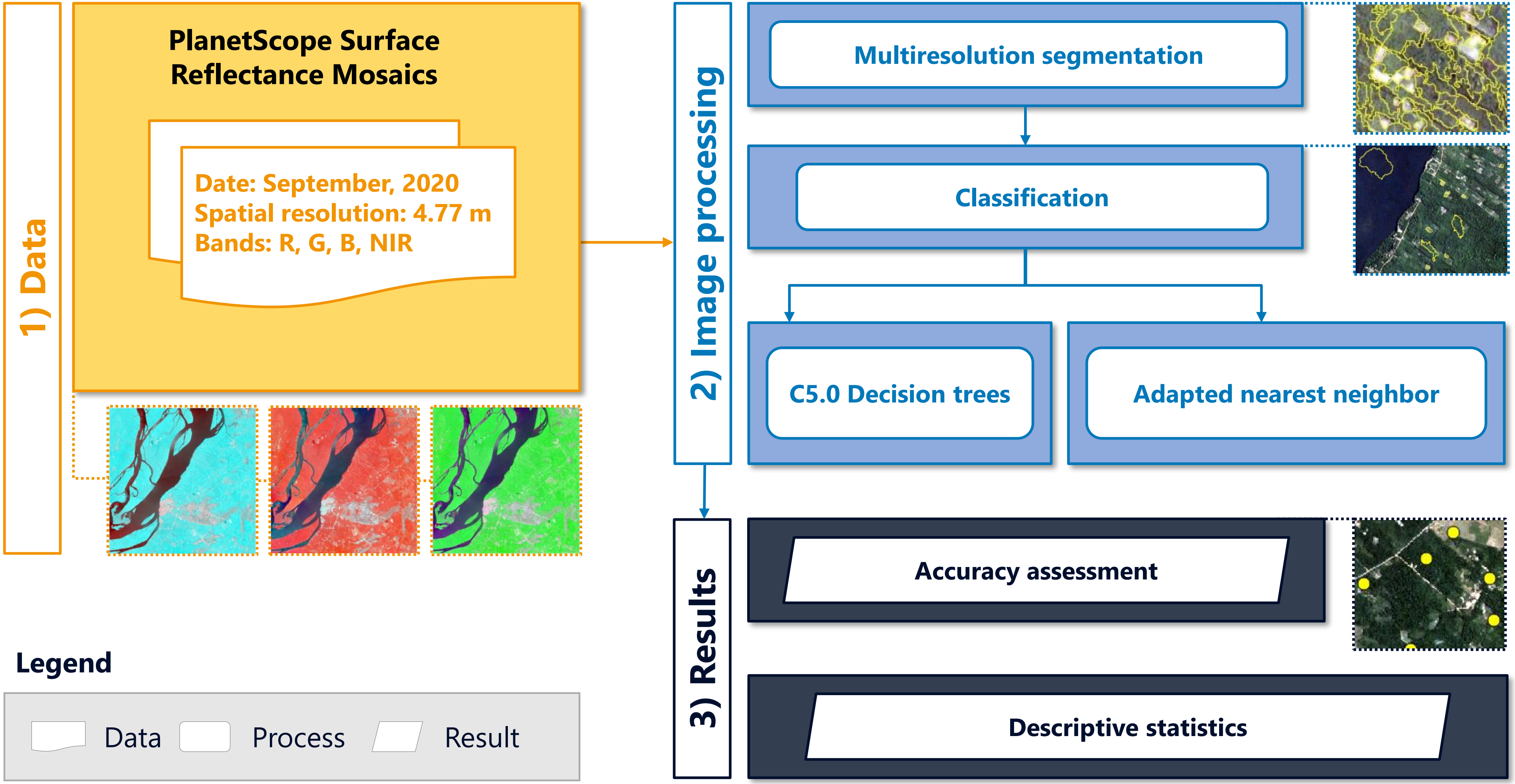
Brazilian Amazon: Mocajuba and Cametá municipalities, Baixo Tocantins region, Northeast of Pará State

Hotspot: smallholders and secondary vegetation

Shifting cultivation: system with swidden-fallow cycles

Main crops: cassava and açaí




1) Data
PlanetScope Surface Reflectance Mosaics
Date: September, 2020
Spatial resolution: 4.77 m
Bands: R, G, B, NIR
2) Image processing
Multiresolution segmentation
Classification
C5.0 Decision trees
Adapted nearest neighbor
3) Results
Accuracy assessment
Descriptive statistics
Legend
Data
Process
Result

Water
Rivers, lagoons, etc.

Forest
Natural vegetation with predominance of trees

Secondary vegetation
Natural vegetation in regeneration emerged from previously deforested areas, with trees, shrubs and herbs

Urban areas
Built-up areas with population clusters: city, village and community

Pasture
Predominance of herbaceous and grassy vegetation, it may occur also sparse shrub vegetation and few arboreal individuals

Small-scale agriculture
Small agriculture lands with mainly annual crops

Others
Aggregate of land use and land cover, such as rocky outcrops, sand banks

Non observed
Clouds and cloud shadows

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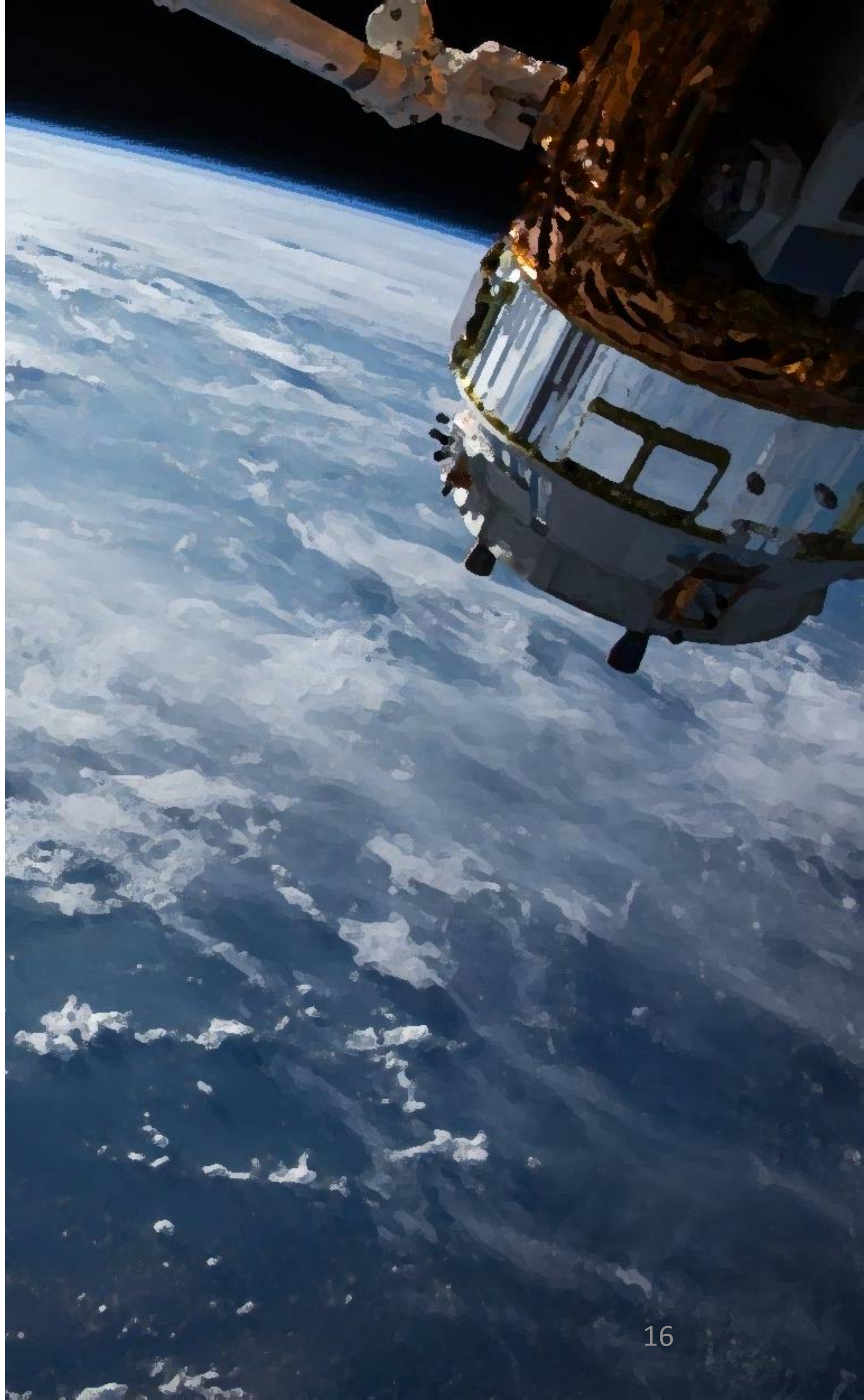

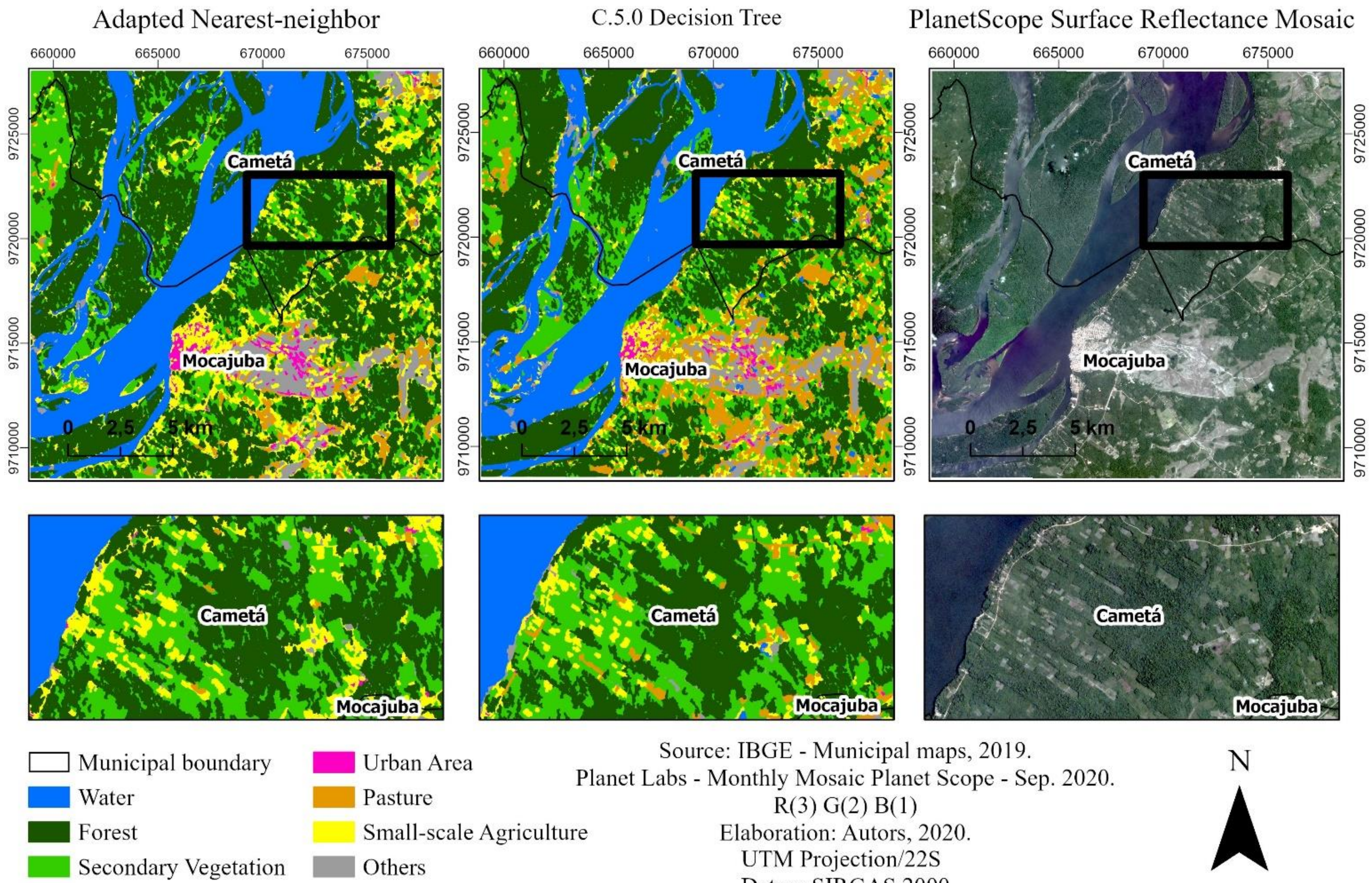

Source: IBGE - Municipal maps, 2019.
Planet Labs - Monthly Mosaic Planet Scope - Sep. 2020.
R(3) G(2) B(1)
Elaboration: Autors, 2020.
UTM Projection/22S
Datum SIRGAS 2000

Descriptive Statistics from image classification according to land use and land cover, in hectare

Classes	Adapted Nearest-neighbor					C5.0 Decision trees				
	μ	*σ*	*σ²*	*Total*	*%*	*μ*	*σ*	*σ²*	*Total*	*%*
Water	5.69	5.62	31.62	7,082.61	18.66	5.92	5.75	33.01	6,885.70	18.14
Forest	1.55	1.18	1.40	11,317.54	29.82	1.62	1.26	1.58	10,477.20	27.60
Secondary vegetation	1.71	1.27	1.61	11,182.62	29.46	1.58	1.18	1.39	11,934.05	31.44
Urban Area	0.69	0.60	0.36	633.66	1.67	0.70	0.63	0.40	537.14	1.42
Pasture	1.77	1.34	1.79	718.84	1.89	1.77	1.10	1.21	2,340.14	6.17
Small-scale agriculture	0.97	0.69	0.48	3,526.97	9.29	0.70	0.39	0.15	1,837.95	4.84
Others	1.22	1.37	1.88	3,493.84	9.20	1.38	1.38	1.92	3,943.92	10.39
Total	-	-	-	37,956.08	100	-	-	-	37,956.08	100

Units: hectare; μ = polygon mean area; σ = standard deviation; σ² = variance.

Confusion Matrix for Adapted Nearest-neighbor and C5.0 Decision Trees algorithms

Adapted Nearest-neighbor

%		*Reference*							
		(A)	(B)	(C)	(D)	(E)	(F)	(G)	User's accuracy
Classification	(A) Water	**100**	0	0	0	0	0	0	100
	(B) Forest	0	**55**	35	0	0	0	0	61
	(C) Secondary vegetation	0	40	**60**	0	0	15	0	52
	(D) Urban area	0	0	0	**95**	0	0	0	100
	(E) Pasture	0	0	0	0	**50**	10	10	20
	(F) Small-scale agriculture	0	5	5	0	50	**65**	0	81
	(G) Others	0	0	0	5	0	10	**90**	86
	Producer's accuracy	100	55	60	95	50	65	90	
	Samples	20	20	20	20	2	20	20	
	Kappa = 0,70				*Overall accuracy = 75%*				

C5.0 Decision trees

%		*Reference*							
		(A)	(B)	(C)	(D)	(E)	(F)	(G)	User's accuracy
Classification	(A)	**90**	0	0	0	0	0	0	100
	(B)	0	**50**	30	0	0	0	0	63
	(C)	0	45	**60**	0	0	15	0	50
	(D)	0	0	0	**85**	0	0	5	94
	(E)	0	0	10	15	**100**	10	20	15
	(F)	0	0	0	0	0	**75**	0	100
	(G)	10	5	0	0	0	0	**75**	83
	Prod. acc.	90	50	60	85	100	75	75	
	Samples	20	20	20	20	2	20	20	
	Kappa = 0,68				*Overall accuracy = 73%*				

High spatial resolution sensors are more adequate to improve classification accuracy due to the small-scale agriculture's size: our results presented mean area of **0.97 ha** ± 0.69 ha for Adapted Nearest-neighbor and **0.70 ha** ± 0.39 ha for C5.0 Decision trees.

Adapted Nearest-neighbor may be overclassifying small-scale agriculture: this method had a **commission error** of 19%, which means that a significant number of polygons were classified by mistake as small-scale agriculture, increasing the area of this class. These classification errors occurred due to confusion, especially with **secondary vegetation, forest, and others.**

C5.0 Decision trees did not have commission error for small-scale agriculture class. In other words, this method is more conservative for mapping small-scale agriculture and did not included other classes in small-scale agriculture by mistake as Adapted Nearest-neighbor did.

Both algorithms had the same **omission errors** for small-scale agriculture regarding **secondary vegetation** (15%) and **pasture** (10%). **Adapted Nearest-neighbor** also had omission errors for small-scale agriculture with the class **others** (10%).

C5.0 Decision trees algorithm found better results when mapping small-scale agriculture (75%), compared to Adapted Nearest-neighbor (65%). This performance of Adapted Nearest-neighbor algorithm is corroborated with other studies that found around 62% of producer's accuracy for small-scale agriculture carried out in the same region of Brazilian Amazon.

Overall, the results for small-scale agriculture were adequate and despite the different accuracies, both methods showed limitations when differentiating this class from pasture and secondary vegetation.

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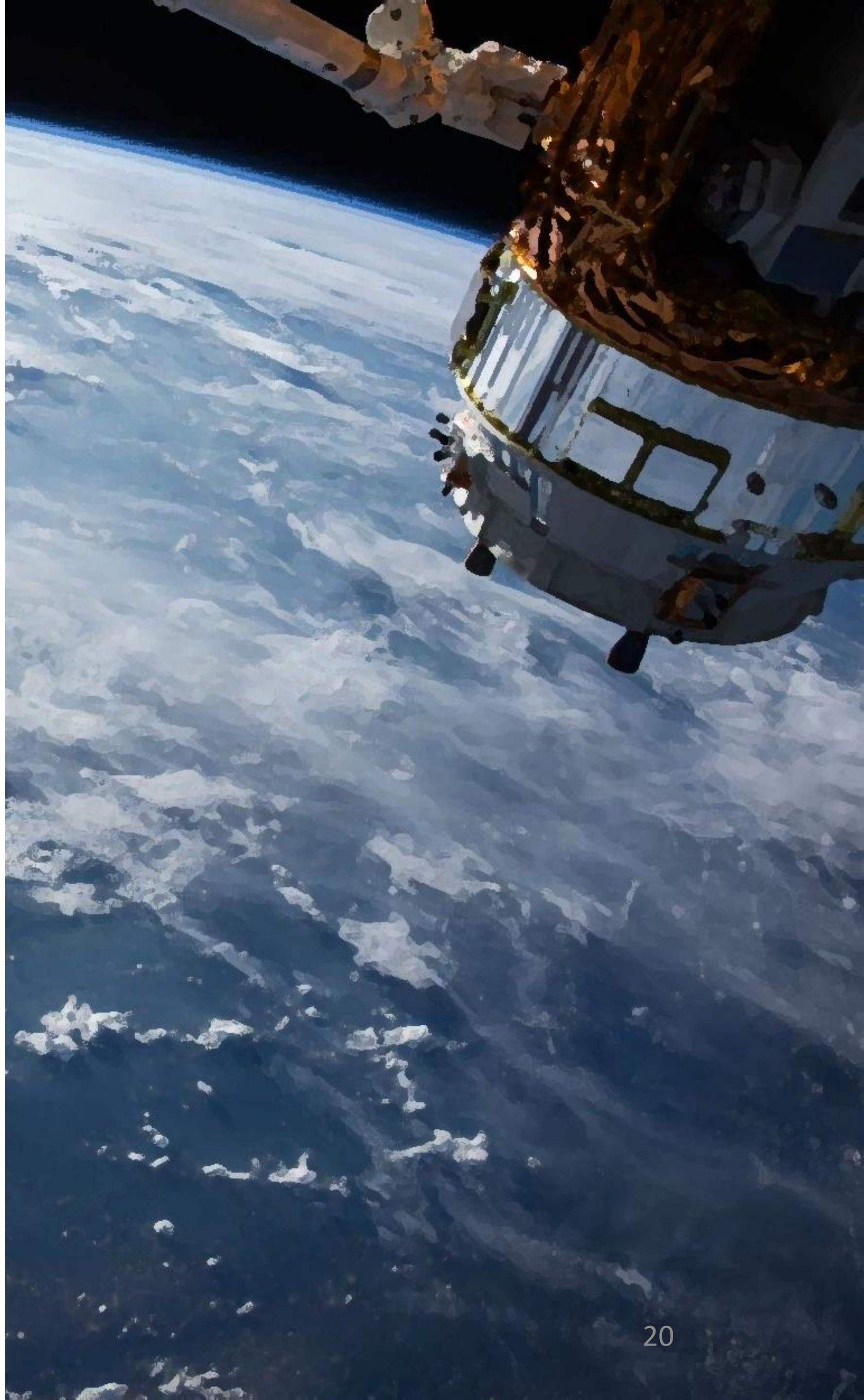

Challenges: use of same training and test samples to promote an adequate comparison

Small-scale agriculture:

C5.0 Decision trees

Higher producer's accuracy

More suitable

Adapted nearest-neighbor

Future work

We recommend investigating which features are more significant for the identification of small-scale agriculture by C5.0. We suggest a systematically removal of features at the classification level and performing a sensitive analysis.

The inclusion of the temporal component coupled with machine learning and deep learning techniques may contribute for selecting other important variables for small-scale agriculture classification.

We recommend testing different sampling design to test better results and perform a sensitive analysis.

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INPE

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Main literature

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Thank you for your attention!

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