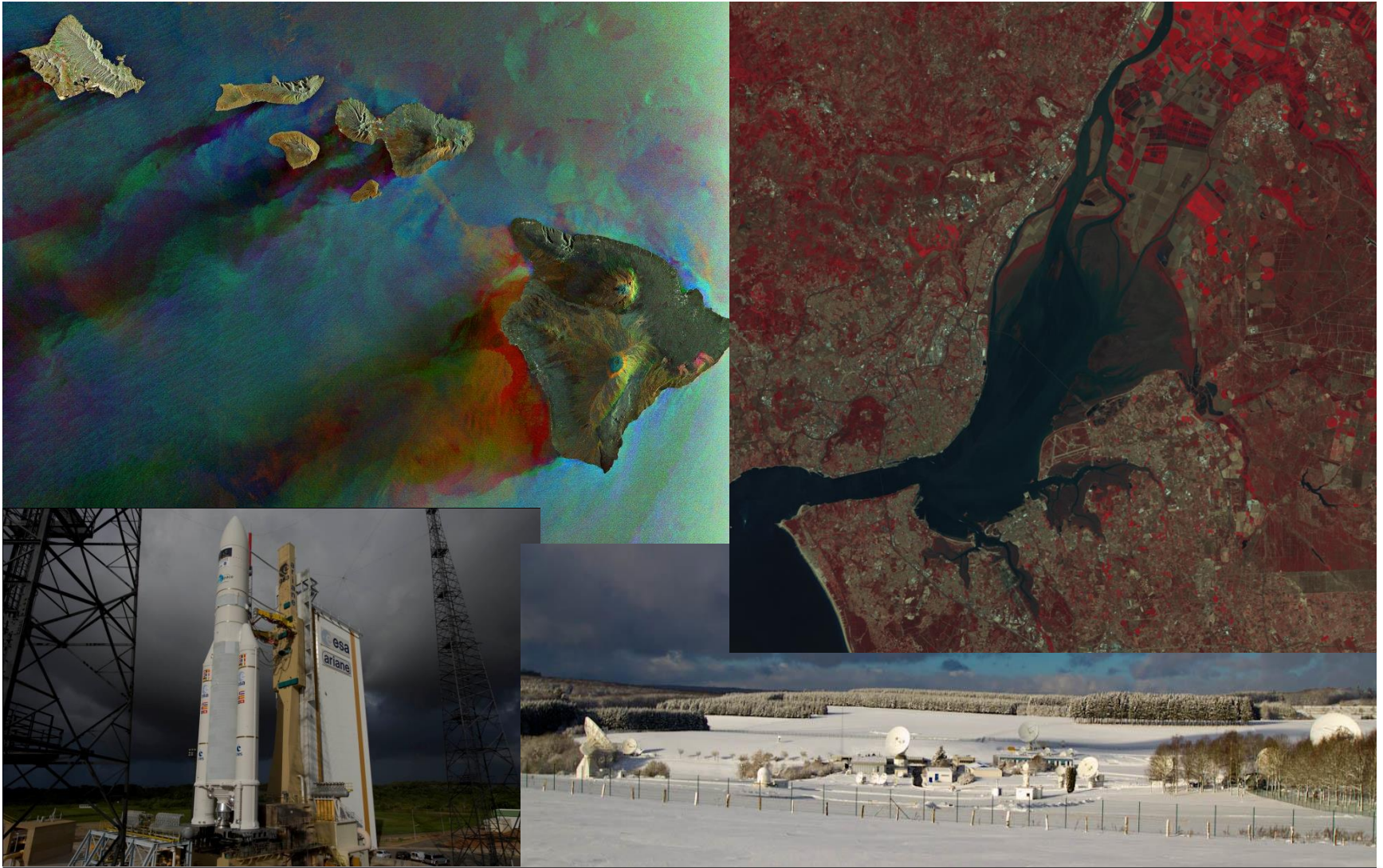




DETECÇÃO REMOTA MULTIESPETRAL





Programa -Teórica

Cap. 1 A Detecção Remota

Cap. 2 Satélites e Sensores

Cap. 3 Princípios Físicos da Detecção Remota

Cap. 4 Classificação Temática

Cap. 5 Aprendizagem Automática

Capitulo 1 – A Detecção Remota

- O que é da Detecção Remota
- Radiação Electromagnética
- Interacção com atmosfera
- Interacção Radiação-Alvo
- Assinatura Espectral
- Detecção Passiva vs Activa
- Sensores Ópticos
- Características das imagens
- Resolução Espacial, Espectral, Radiométrica e Temporal
- Formato dos dados
- Sistemas de imagens

Capítulo 2 – Satélites e Sensores

- Satélites Meteorológicos
 - GOES, NOAA AVHRR, Outros satélites
- Satélites de Observação do Mar
- Altimetria Espacial
- Missões Geopotenciais Espaciais
- Missões LIDAR
- Missões SAR
- Missões na banda do visível
 - LANSAT, SPOT, IRS, IKONOS, QuickBird, GeoEye-1

Capítulo 3 – Princípios Físicos da Detecção Remota

- Ondas eletromagnéticas e Equação de Maxwell
- Polarização e Interferência das ondas eletromagnéticas
- O espectro eletromagnético
- Fontes de radiação eletromagnética
- Quantidades radiométricas
- Interação da radiação eletromagnética com a matéria
- Interação da radiação eletromagnética com a atmosfera
- Conversão números digitais para radiância
- Distorção e correção geométrica das imagens

Capitulo 4 – Classificação Temática

- Índices (empíricos) de Vegetação
- O processo de classificação
- Classificação de Máxima Verosimilhança (supervisionada paramétrica)
- Classificador Distância mínima
- Classificador Paralelepípedo
- Classificador Mahalanobis
- Método não supervisionado



Capitulo 5 – Aprendizagem automática

- Aprendizagem automática (Machine Learning)
- Classificação binária
- Conceito de aprendizagem
- Modelos em árvore (decision tree, random forest)
- Modelos lineares (Perceptron, SVM,
- Modelos baseados na distancia (NN, K.means)
- Convolutional Neural Networks



Avaliação / assessment

Exame Escrito	50%
Apresentação e discussão de um artigo científico	10%
Relatório do trabalho prático:	40%

A data limite para entrega do trabalho prático é **?? maio de 2022**.
Haverá uma apresentação oral do trabalho.



Trabalho Prático

Realização de um projecto de detecção remota (a ser definido)

Artigo Científico

Artigo sobre o uso de inteligência artificial na classificação de imagem.
Keywords: Machine learning, Deep learning, Neural networks, CNN

Calendarização das aulas Teóricas

Data	Descrição
22 fev.	Apresentação da Disciplina. Avaliação.
1 março	Carnaval
8 março	A Deteção Remota
15 março	A Deteção Remota
22 março	Satélites e Sensores: Missões na banda do visível: LANSAT, SPOT, IRS, IKONOS, QuickBird, GeoEye-1
29 março	Satélites e Sensores: Satélites Meteorológicos: GOES, NOAA AVHRR, Outros satélites, Altimetria Espacial, Missões Geopotenciais Espaciais
5 abril	Princípios Físicos da Deteção Remota
12 abril	Princípios Físicos da Deteção Remota
19 abril	Páscoa
26 abril	Classificação Imagem
3 maio	Classificação Imagem (exercícios)
10 maio	Aprendizagem automática
17 maio	Apresentação pelos alunos de um artigo científico
24 maio	Apresentação pelos alunos de um artigo científico

Bibliografia

- Fundamentals of Remote Sensing, Canada Centre for Remote Sensing. http://www.ccrs.nrcan.gc.ca/resource/tutor/fundam/index_e.php
- Ana Duarte Fonseca, João Cordeiro Fernandes, "Detecção Remota". LIDEL.
- R.A. Schowengerdt, "Remote Sensing. Models and Methods for Image Processing", Academic Press ed.
- Remote Sensing Digital Image Analysis, An Introduction. Hohn A. Richards. Springer-Verlag.
- Principles and Applications of Imaging Radar. Manual of Remote Sensing, Third Edition, Vol. 2. Edited by Floyd M. Henderson and Anthony J. Lewis.
- Remote Sensing of the Earth Sciences. Manual of Remote Sensing, Third Edition, Vol. 3. Edited by Andrew N. Rencz.



Agencias Espaciais

www.esa.int

European Space Agency

www.nasa.gov

National Aeronautics and Space Administration

www.dlr.de

Deutsches Zentrum für Luft- und Raumfahrt

www.nasda.go.jp

National Space Development Agency of Japan

www.cnes.fr

Centre National d'études Spatiales

www.space.gc.ca

Canadian Space Agency

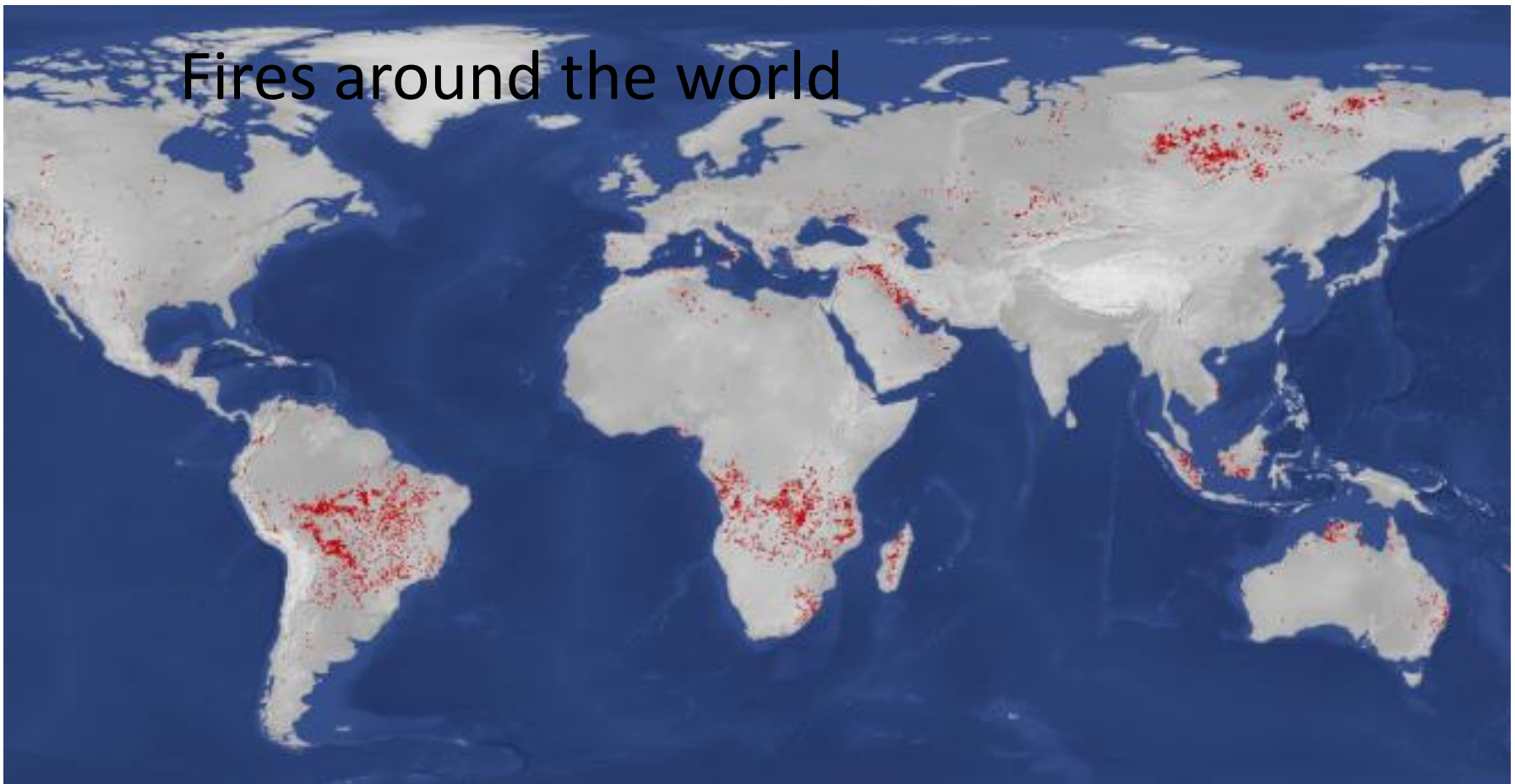
www.bnsc.gov.uk

British National Space Centre

www.isro.org

Indian Space Research Organization

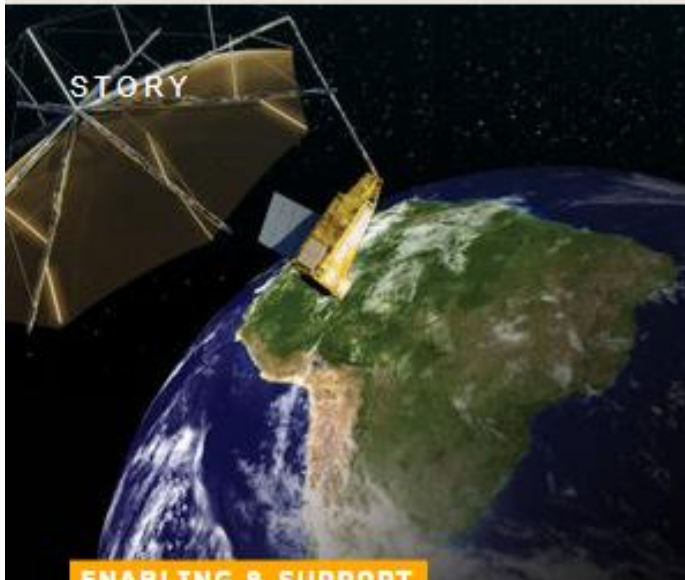
Fires around the world



Data from the Sentinel-3 World Fire Atlas shows that there were almost five times as many wildfires in August 2019 compared to August 2018, but a detailed analysis reveals precisely where these fires have been occurring – most of which were in Asia.

Working like thermometers in the sky, the sensors on satellites measure thermal infrared radiation to take the temperature of Earth's land surfaces. This information is used to detect and monitor the heat emitted by the fires.

BIOMASS



ENABLING & SUPPORT

Key components of tree-counting Biomass radar cleared for s...

16/10/2018 2810 VIEWS 101 LIKES

READ



APPLICATIONS

Ready to build the Biomass forest mission

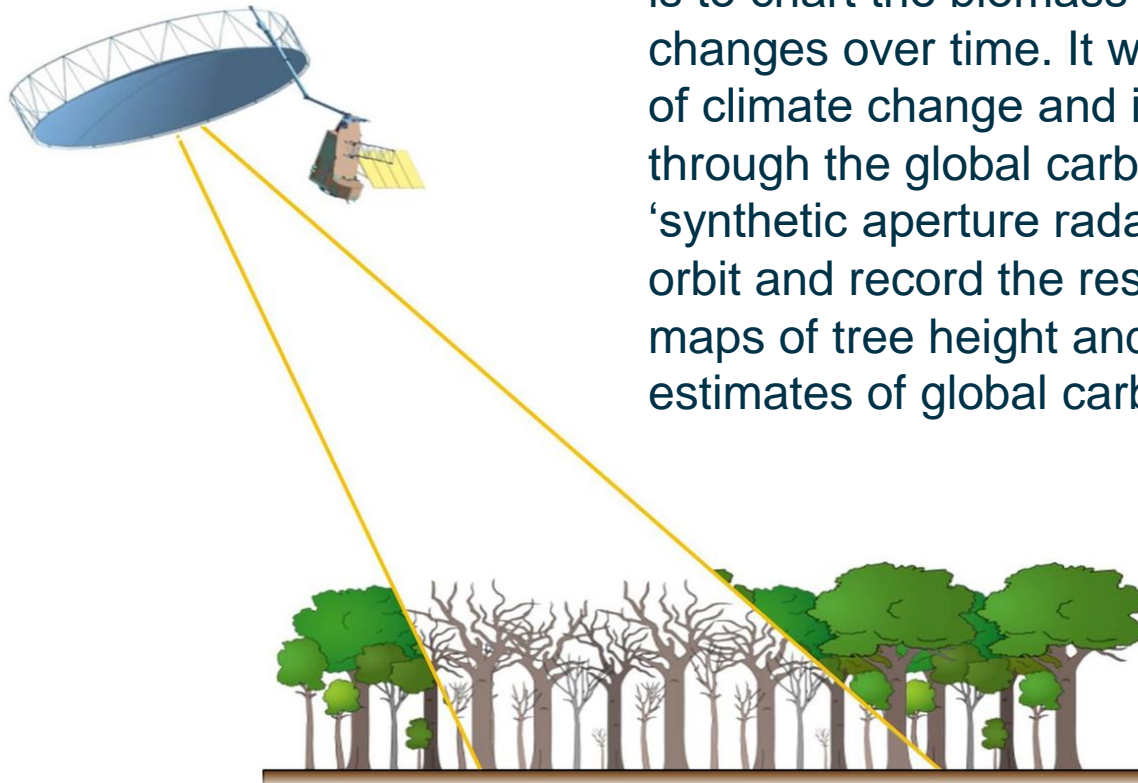
03/05/2016 4456 VIEWS 52 LIKES

READ



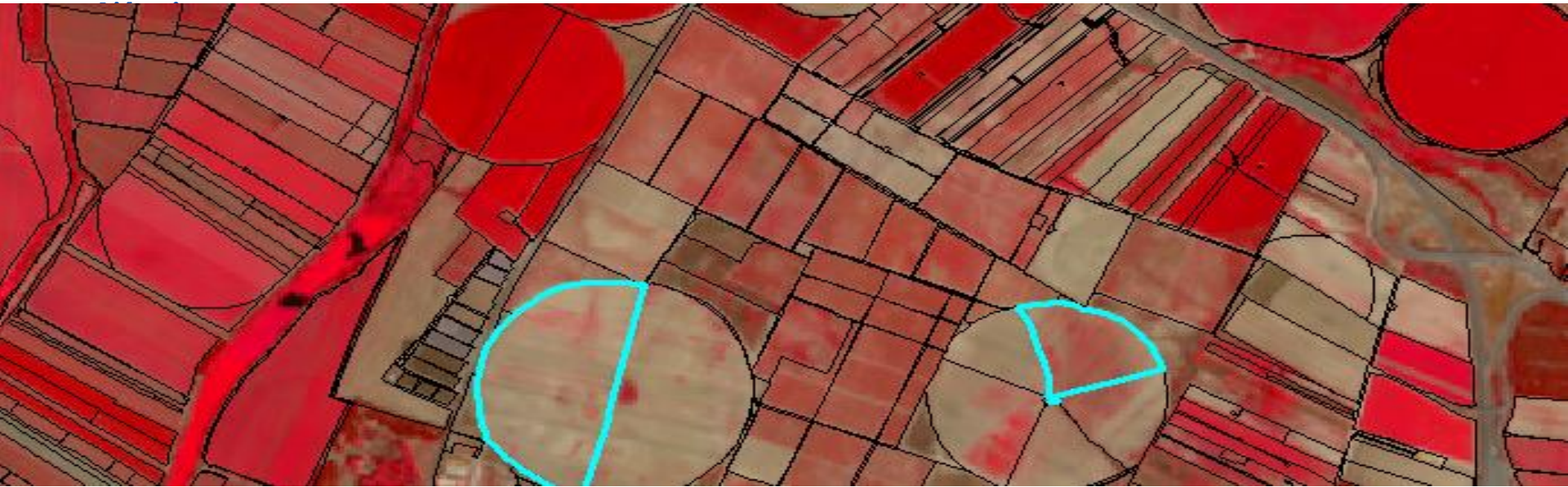
BIOMASS

Due for launch in 2022, Biomass's five-year mission is to chart the biomass of Earth's forests, and its changes over time. It will contribute to understanding of climate change and its effects on Earth's system through the global carbon cycle. It does this using a 'synthetic aperture radar' to send down signals from orbit and record the resulting backscatter, to build up maps of tree height and volume, and sharpen estimates of global carbon stocks.



To be launch in
2022

To see through leafy treetop to the trees themselves, Biomass will employ long-wavelength 'P-band' radar, which has never previously flown in space. It will have its signals amplified to travel down from a 600-km-altitude orbit down to Earth and back.



Apoio à implementação de um sistema de alerta para monitorização da atividade agrícola com base em imagem de satélite e inteligência artificial

João Catalão, Ana Navarro

IDL, Faculty of Sciences, University of Lisbon, Portugal;



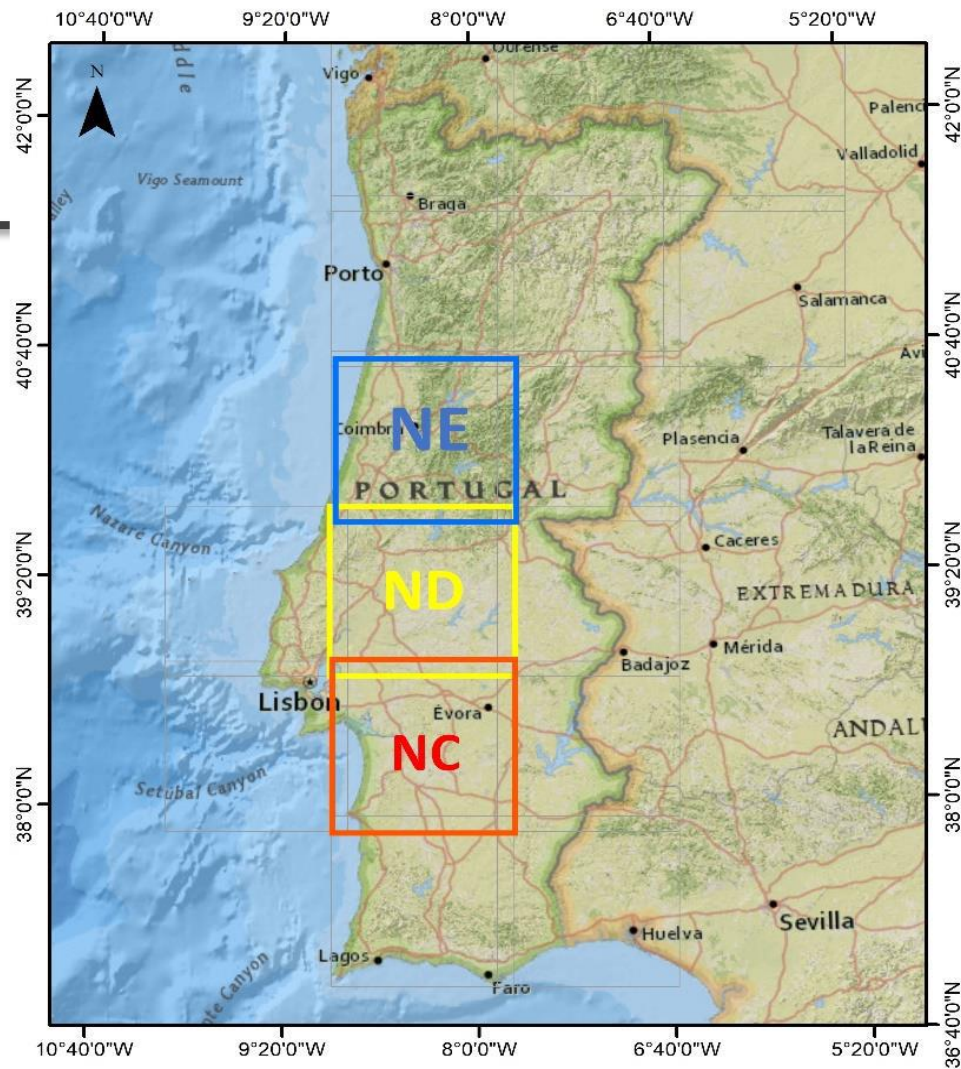
Ciências
ULisboa

CAP, Common Agriculture Policy

- Estudo de marcadores fenológicos de culturas agrícolas relevantes em termos da monitorização da ocupação do solo;
 - Desenvolvimento de uma metodologia que valide a candidatura do agricultor em termos da sua conformidade, e não conformidade ou dúvida;
 - Prototipagem do sistema de implementação do modelo;
-



Ciências
ULisboa



0 25 50 100 150 200 km

Coordinate System: WGS 1984 UTM Zone 29N
Projection: Transverse Mercator
Datum: WGS 1984
False Easting: 500,000.0000
False Northing: 0.0000
Central Meridian: -9.0000
Scale Factor: 0.9996
Latitude Of Origin: 0.0000
Units: Meter

 Quadrícula Sentinel 2



0 5 10 20 30 40 km

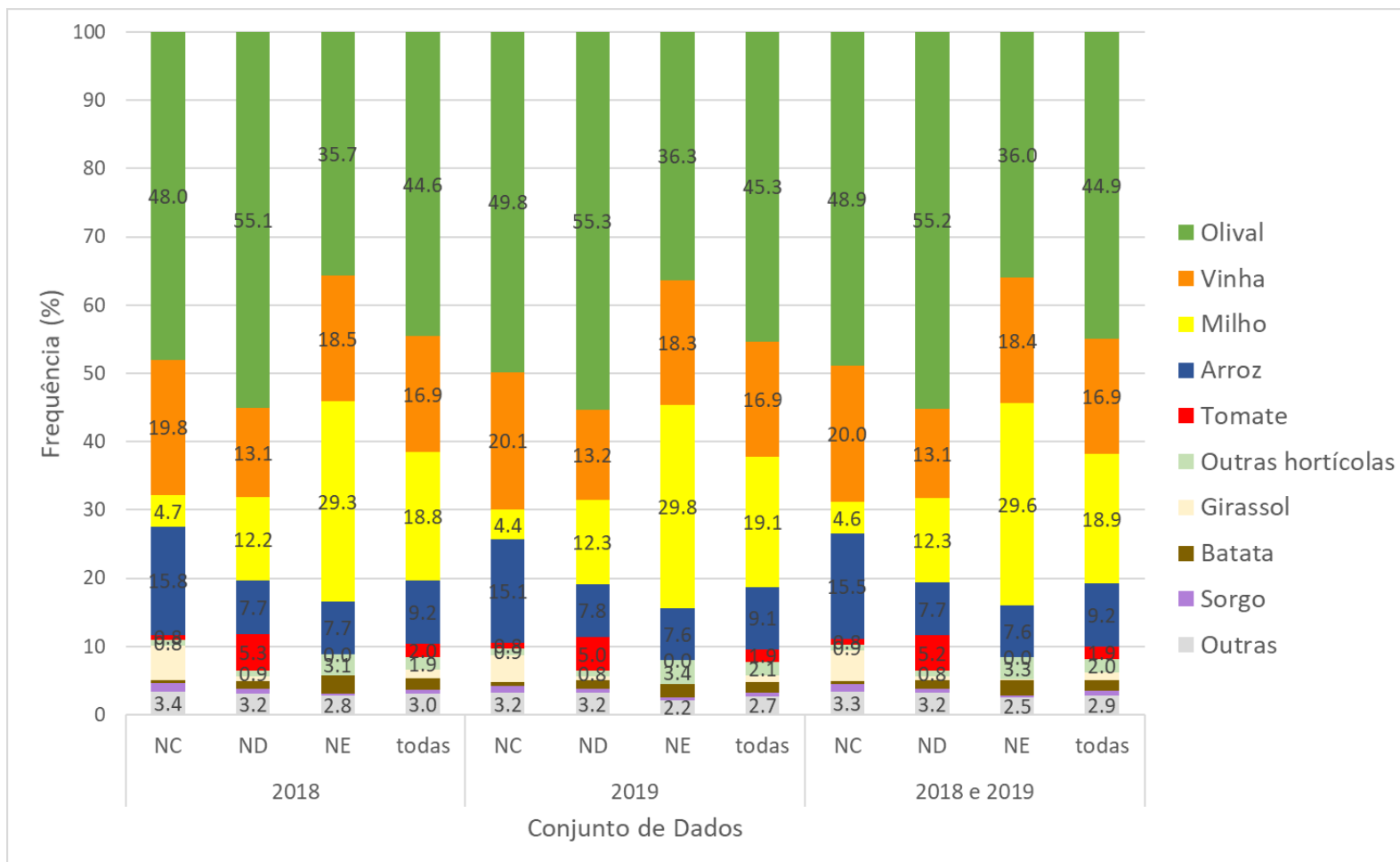


0 5 10 20 30 40 km



0 5 10 20 30 40 km

Distribuição do tipo de culturas por região/ano.





Imagens Sentinel-2 e parcelas

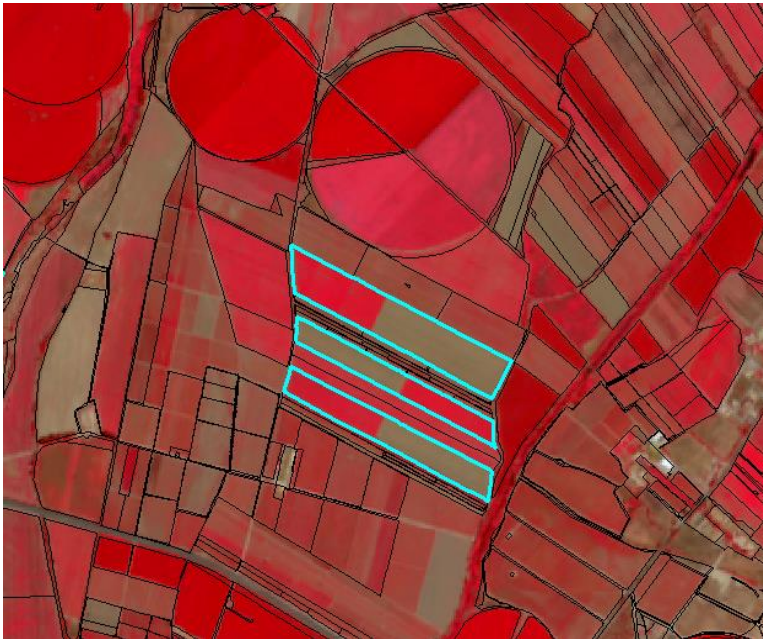
Ano	Zona	Março		Abril			Maio					Junho				Julho				Agosto						Setembro					Outubro		
		21	26	20	25	30	05	10	15	25	30	09	19	24	29	14	19	24	29	03	08	13	18	23	28	02	07	12	22	27	07	12	
2018	NE																																
	ND																																
	NC																																
2019	NE																																
	ND																																
	NC																																

Nome do conjunto de dados (ano, zona geográfica)	N.º de parcelas (amostras)	N.º de variáveis	N.º de Imagens
2018 NE	62335	108	12
2018 ND	44795	90	10
2018 NC	25137	117	13
2019 NE	61980	126	14
2019 ND	44563	162	18
2019 NC	25137	153	17

DESAFIOS / PROBLEMAS



Controlo da atividade agrícola (atividade vegetativa)

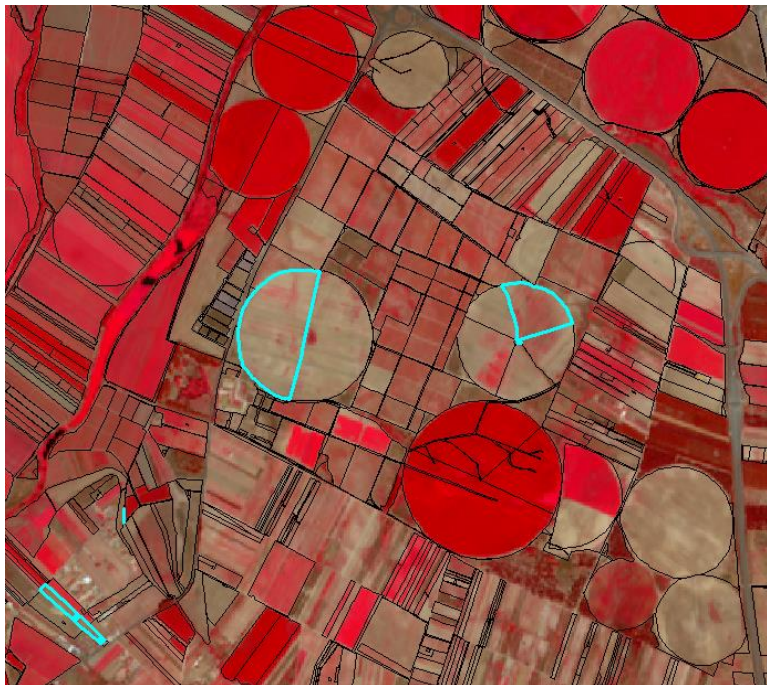


Declarada como Tomate



**Declarada como pastagem permanente
(permanent pasture)**

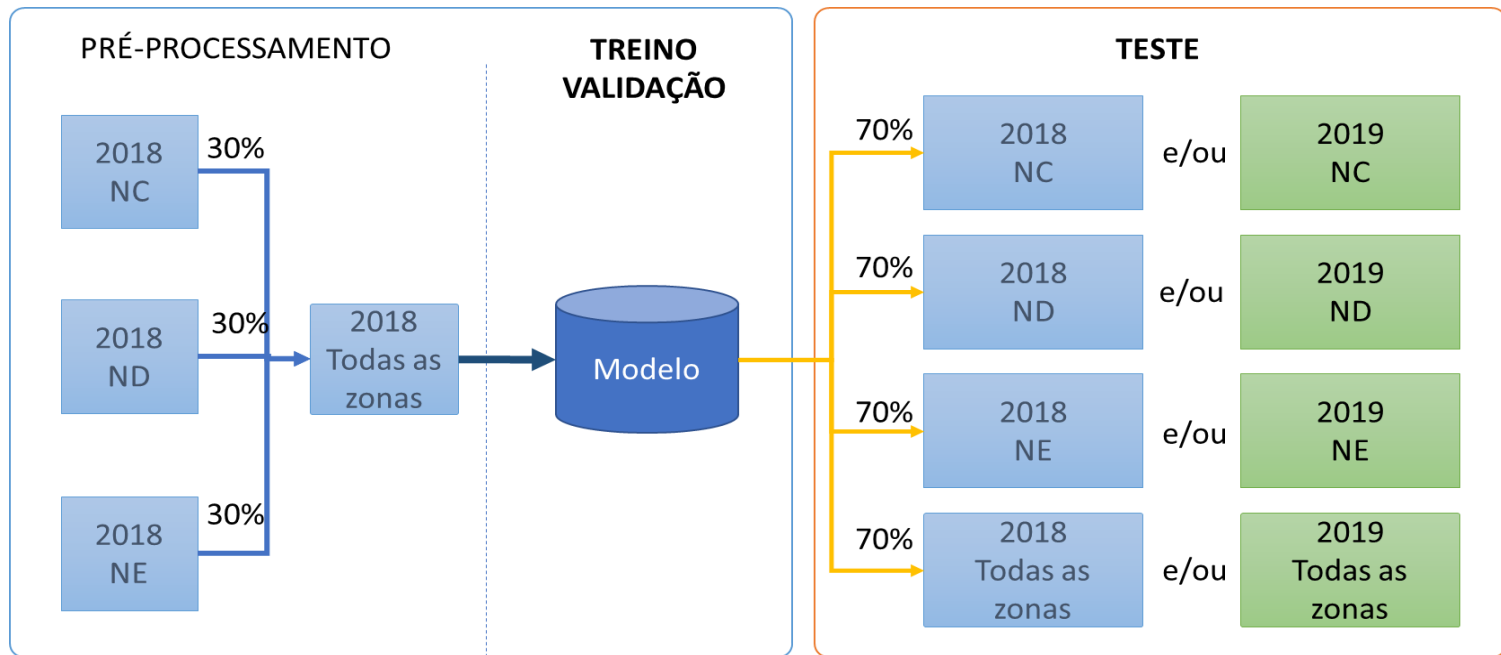
Controlo da atividade agrícola (atividade vegetativa)



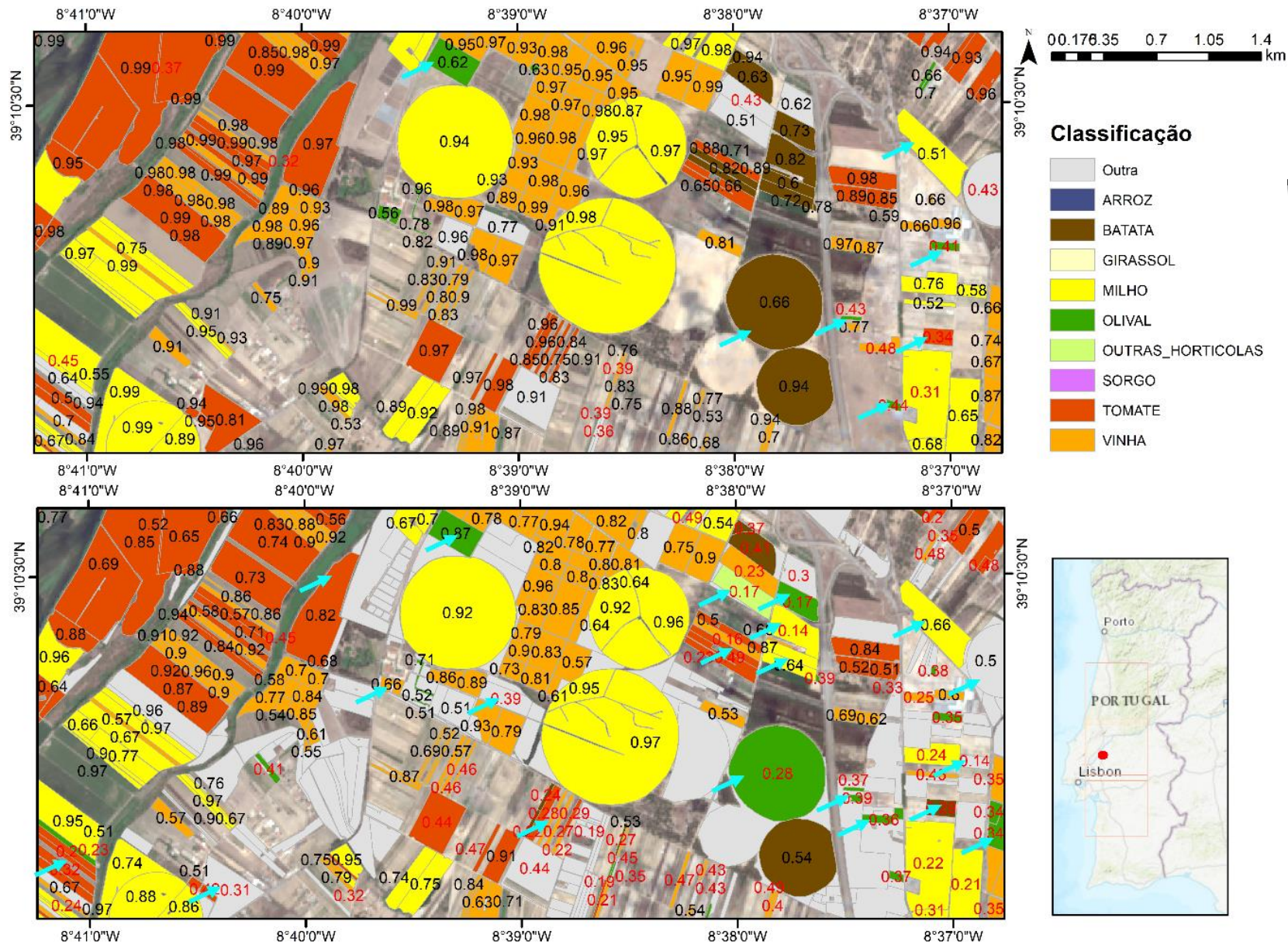
declaradas como Milho (Corn)



Declarado como Milho



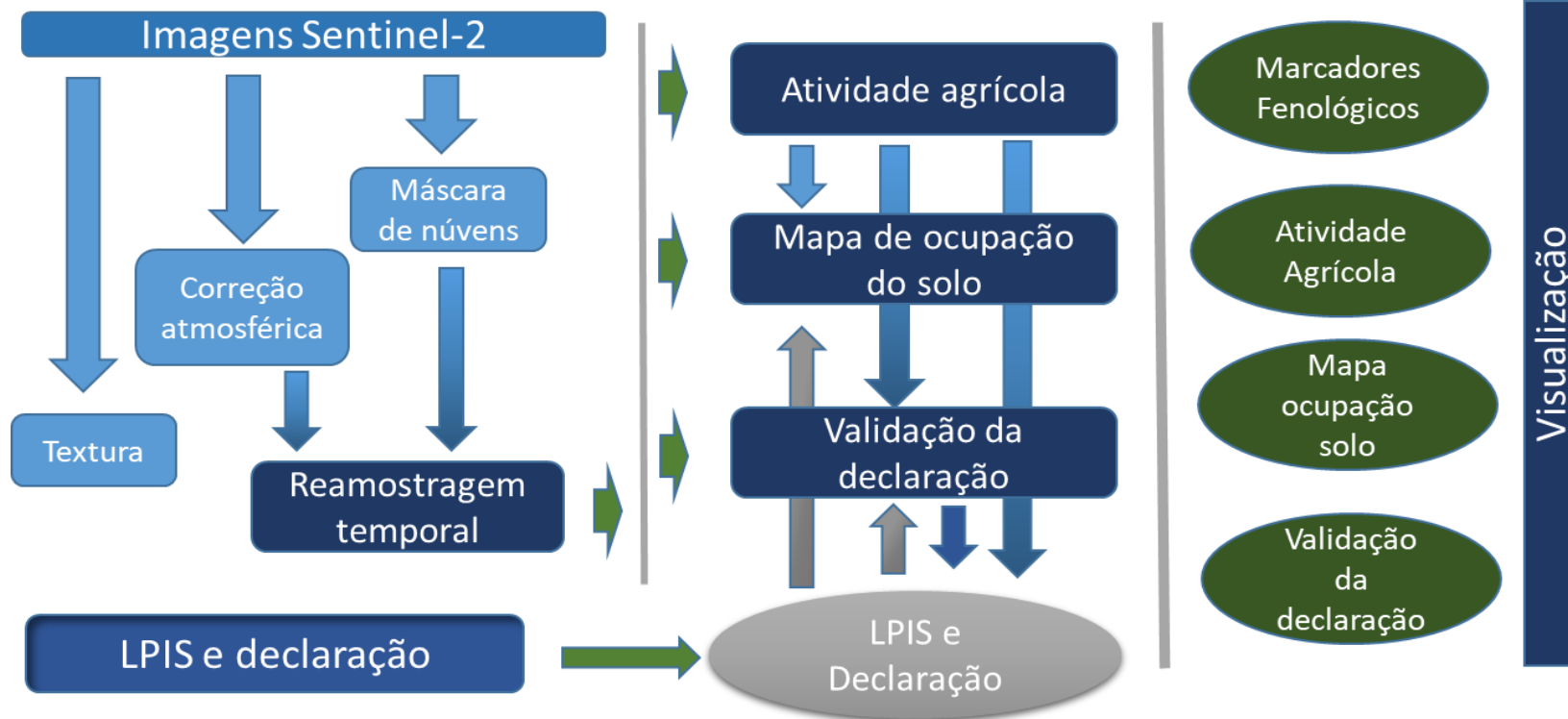
As declarações dos agricultores são usadas para treino do classificador



Mapa de confiança (2019 zona ND) para as mesmas parcelas e para modelo sem TL (T02, em cima) e com TL no tempo (T06, em baixo) (o apontador azul indica parcelas incorretamente classificadas).

O sistema de monitorização SAMAS-IA

SMAS-IA



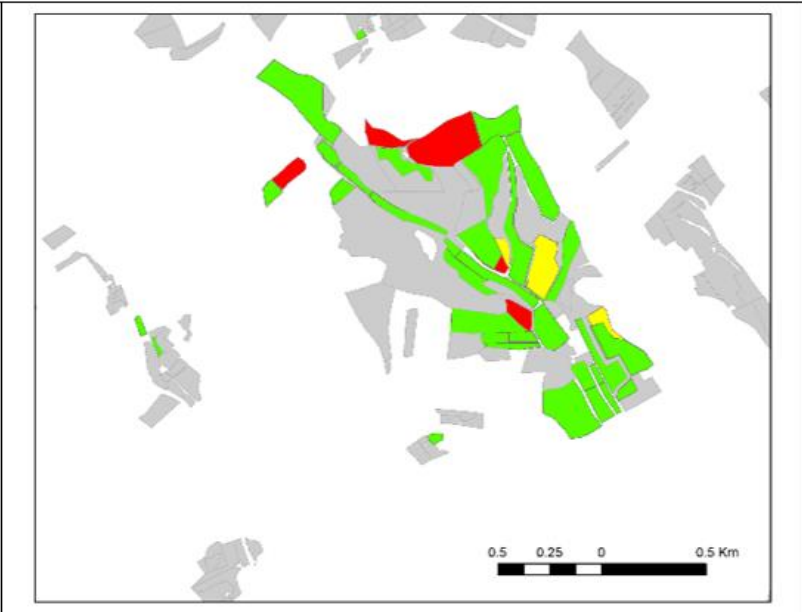
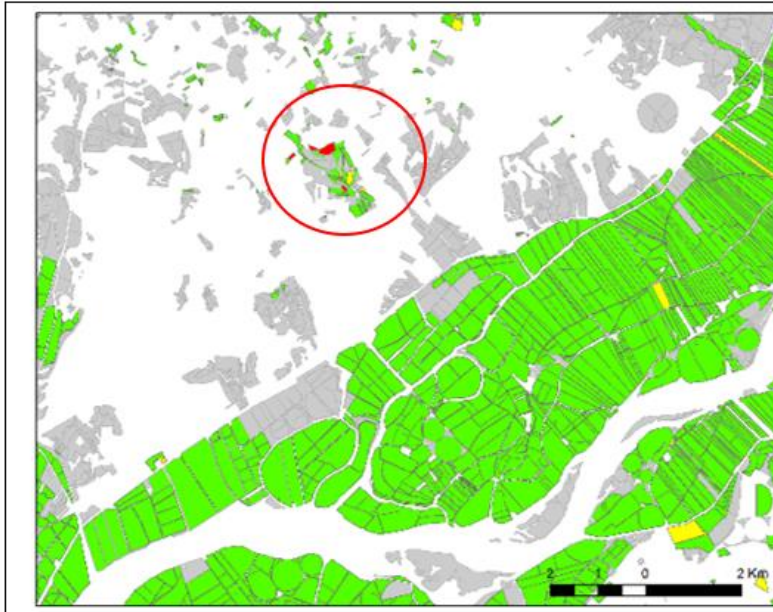
Validação da declaração

Mapa de ocupação do solo

LPIS e declaração

Atividade Agrícola

	Declarado cultura A				Declarado Vinha ou Olival			
	Sim	Não	Sim	Não	Não	Não	Não	Sim
Atividade agrícola	Sim	Não	Sim	Não	Não	Não	Não	Sim
Predito cultura A	Sim	Não	Não	Não	Sim	Não	Não	Não
Predito cultura B		Sim	Sim	Sim		Sim	Sim	Sim
Predito Cultura Temporária		Sim		Não			Sim	Sim
Predito Cultura Permanente			Sim	Sim		Sim		Não





Monitorização do estado vegetativo do sobreiro com imagens multiespectrais do satélite Sentinel-2

João Catalão, Ana Navarro, João Calvão
IDL, Faculty of Sciences, University of Lisbon, Portugal;





Parcelas de referência

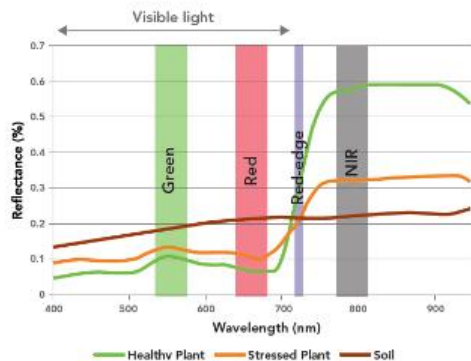
Parcela / Data	referência	2º voo	3º voo
Machoqueira	26 jun 2018	22 out 2018	25 jun 2019
C. Lezírias	12 jul 2018	23 out 2018	27 jun 2019
Freixo	10 jul 2018	24 out 2018	26 jun 2019
Azinhhal	10 jul 2018	24 out 2018	24 jun 2019



Caraterísticas do VANT

- > Sensefly eBee
- > Câmara Sequoia com 4 bandas (Verde, Vermelho, Red-Edge e Infravermelho) + Visível (Azul, Verde e Vermelho)

Green Vegetation Reflectance



* See the list on www.parrot.com

General Specification



Body

- 4 spectral cameras 1.2 Mpx
10 bits Global shutter
- Up to 1 FPS
- RGB Camera 16 Mpx
Rolling shutter
- Configuration over Wi-Fi
- IMU + Magnetometer
- 64 GB
- 5W (~12W peak)
- 72g

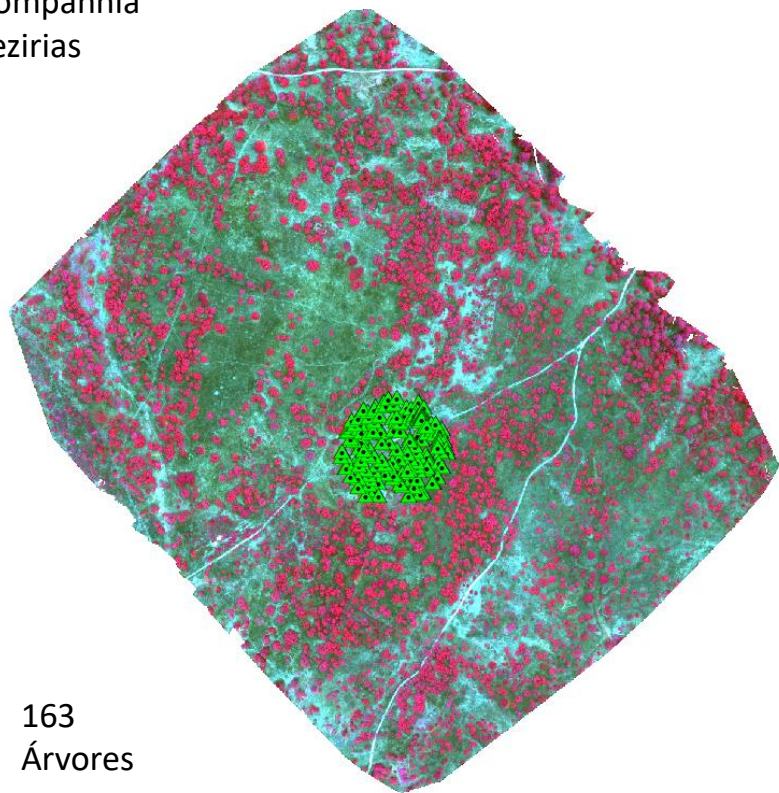
Sunshine sensor

- 4 spectral sensors with
the same filters as
the body
- GPS
- IMU + Magnetometer
- SD Card
- 1W
- 35g



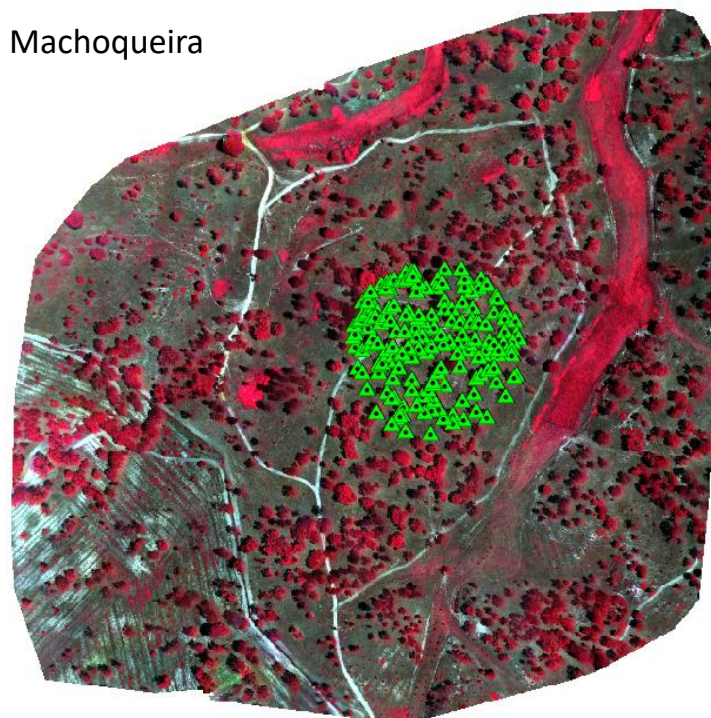


Companhia
Lezirias



163
Árvores

Machoqueira



182 Árvores



Ciências
ULisboa

C. Lezírias, UAV /S2 image



Identificação e georreferenciação de árvores no campo



Ciências
ULisboa

Algoritmo para deteção de árvores

MSP

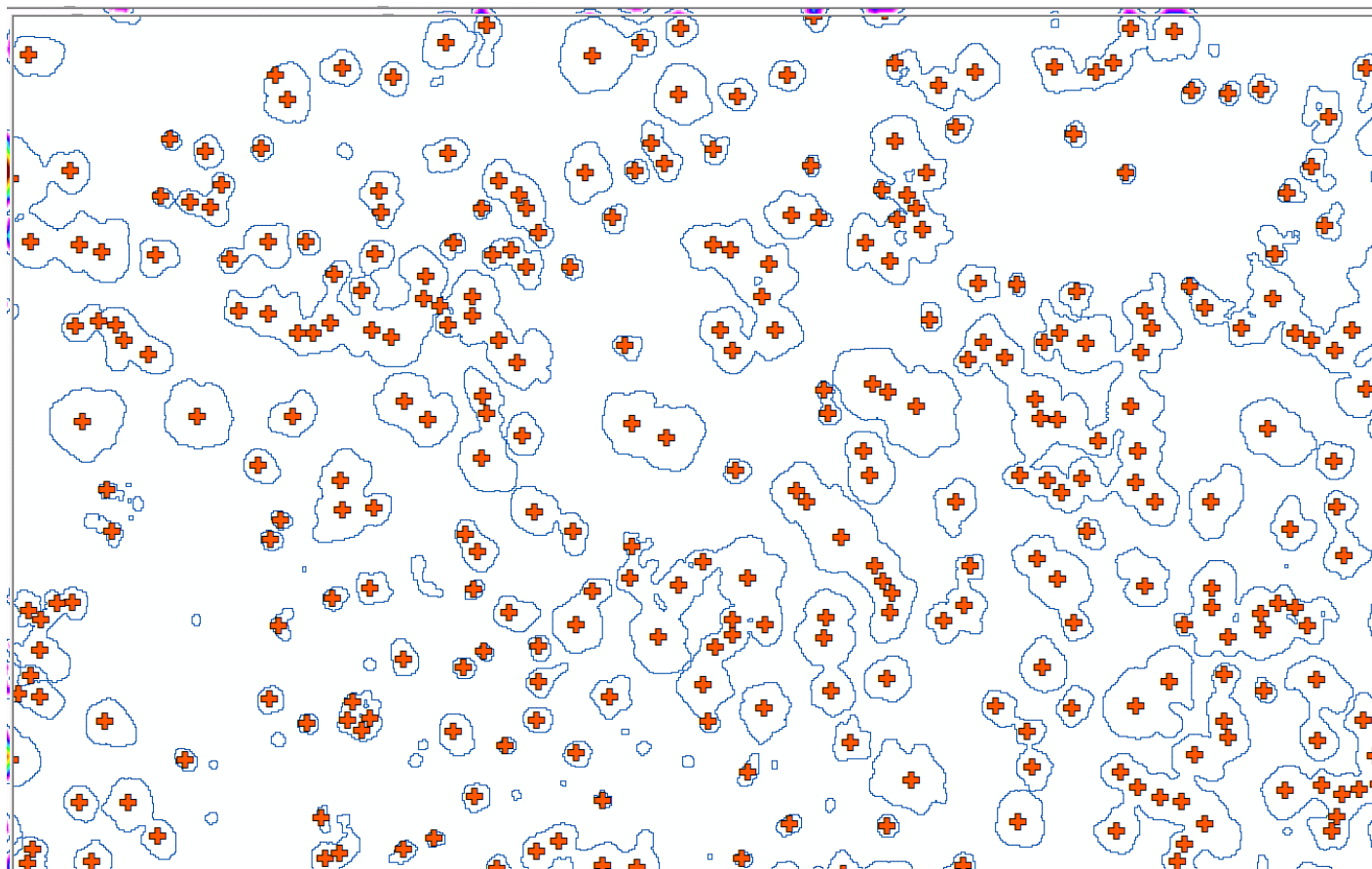
NDVI

Contorno

(Adaptive binarization)

Euclidean
Distance

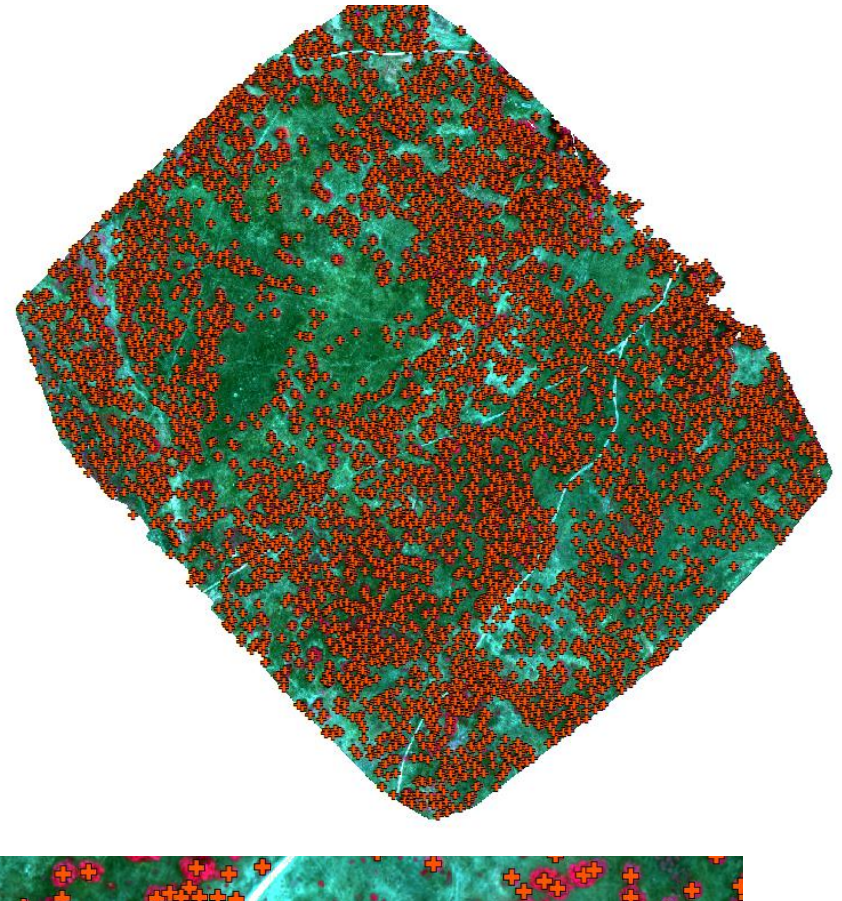
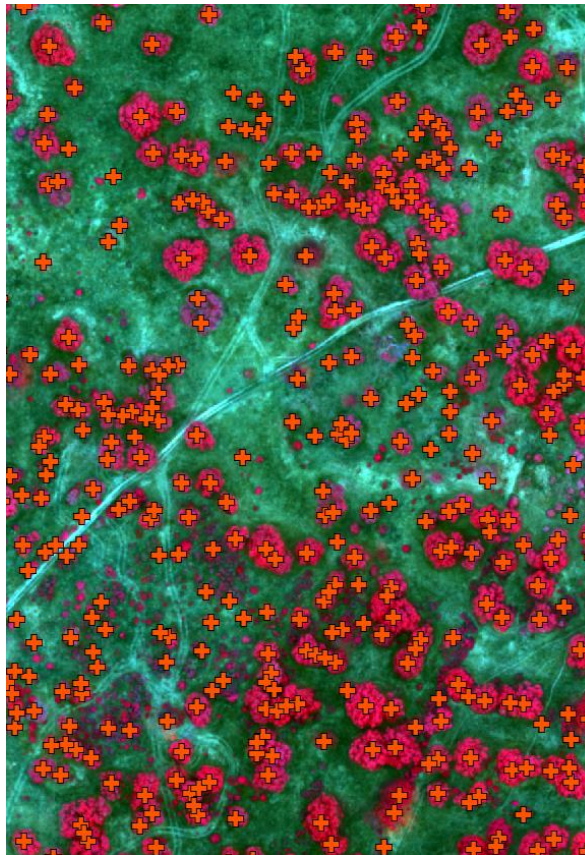
Max Local





Ciências
ULisboa

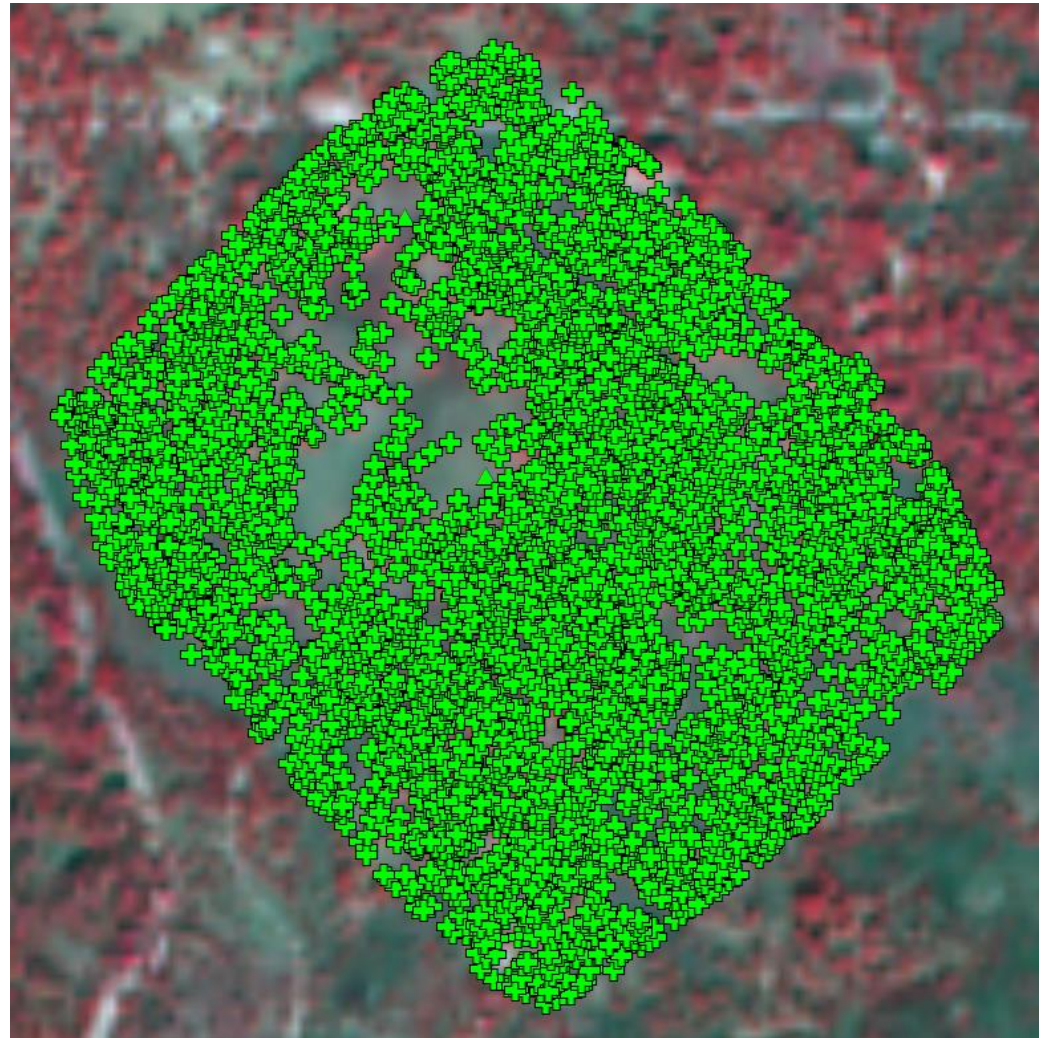
Algoritmo para deteção de árvores





Análise Multitemporal

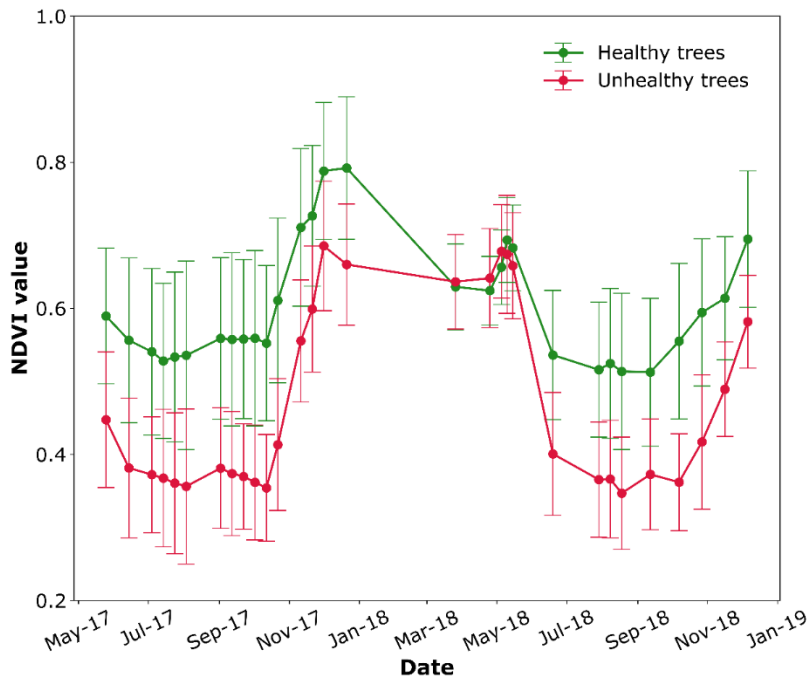
20160808	20170724	20180729
20160818	20170803	20180808
20160828	20170813	20180818
20160907	20170823	20180917
20160917	20170902	20180927
20160927	20170912	
20161007	20170922	
	20171002	
	20171012	
	20171022	



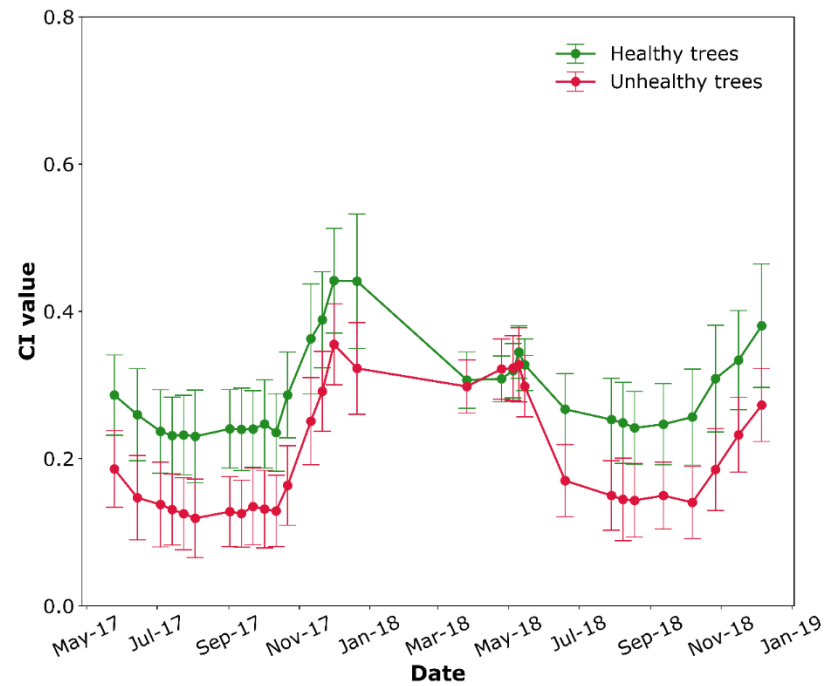


Série temporal dos índices NDVI e RedEdge

NDVI time series



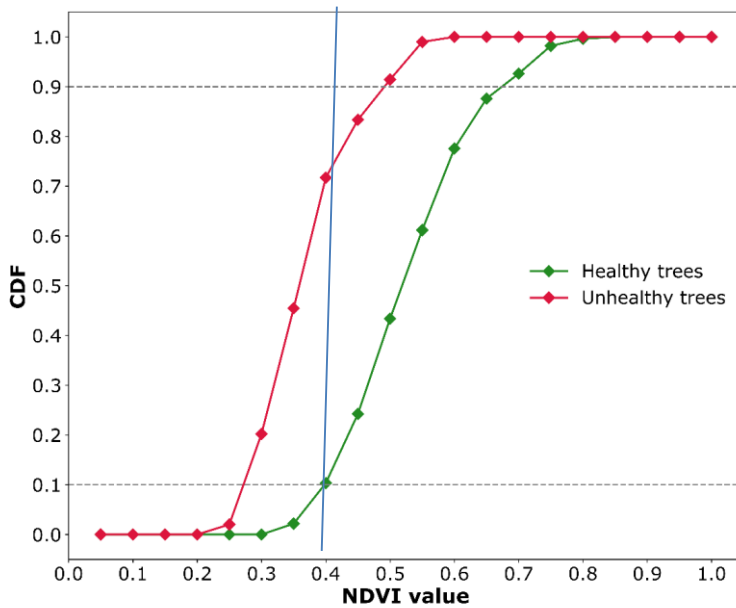
CI time series



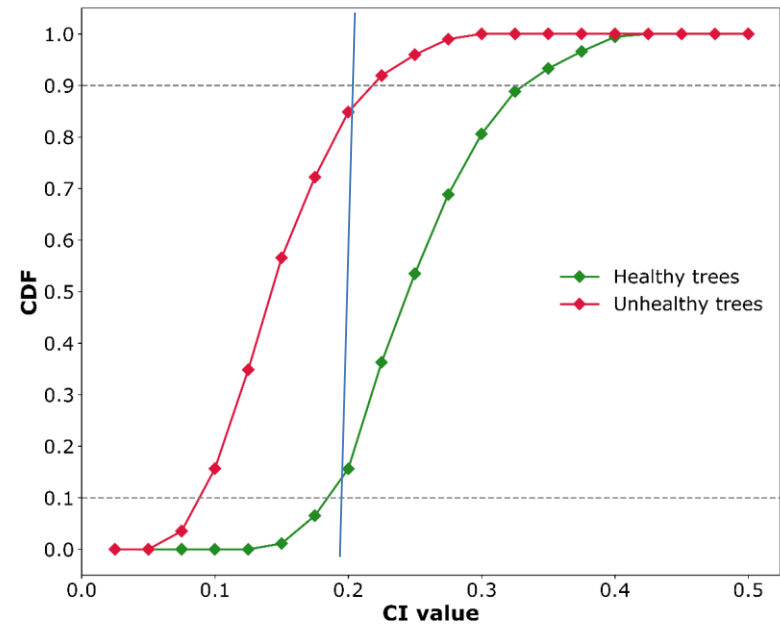


Função distribuição cumulativa do NDVI e RedEdge

NDVI Cumulative Distribution Function



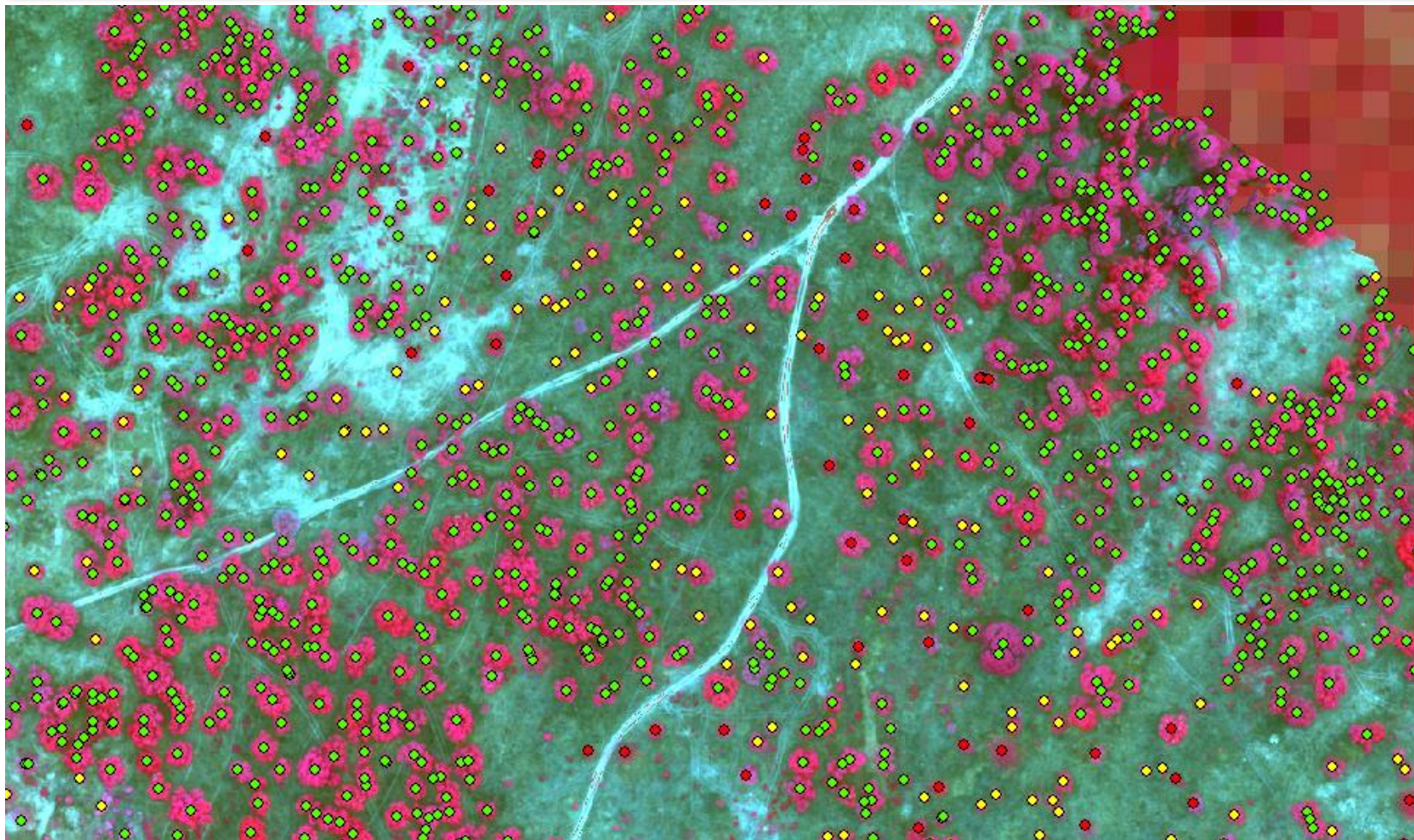
CI Cumulative Distribution Function

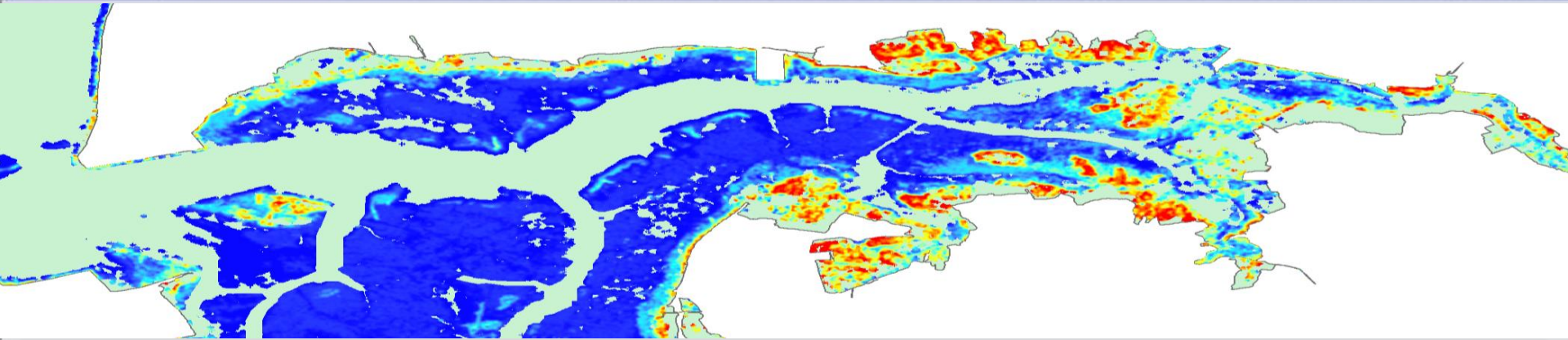




Ciências
ULisboa

Identificação das árvores com redução da atividade vegetativa





Mapping Intertidal morphology by multitemporal SAR backscattering data

Joao Catalao⁽¹⁾ & Giovanni Nico⁽²⁾

1: IDL, Faculty of Sciences, University of Lisbon, Portugal;

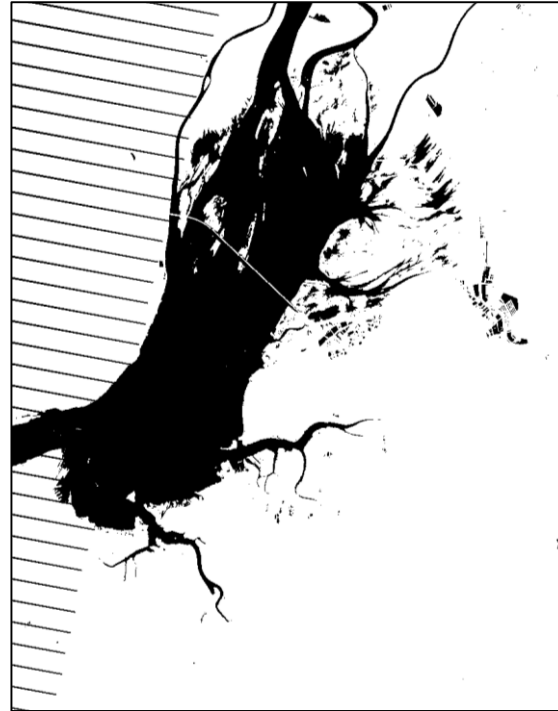
2: CNR, Istituto per le Applicazioni del Calcolo (IAC) - Bari, Italy



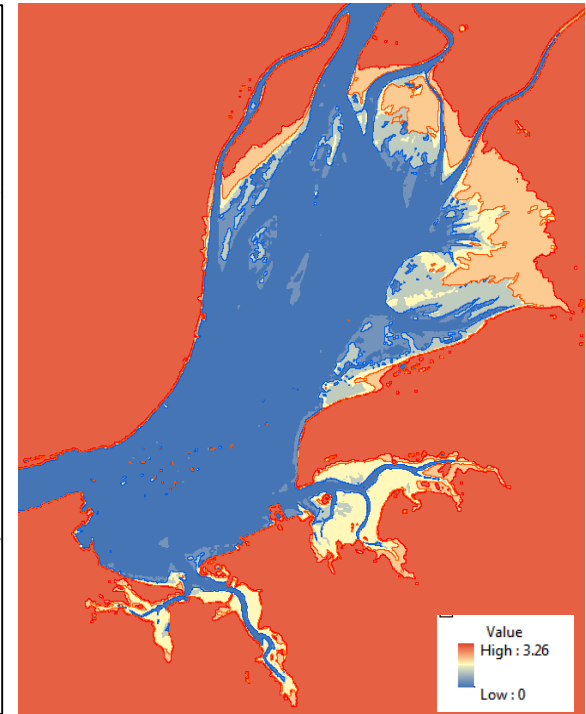


Mapping Intertidal morphology

Waterline Method



Water level = 0.69 m
Date: 31 Aug. 2007





Ciências
ULisboa

Mapping Intertidal morphology

Waterline Method for SAR (*)



- Thresholding
- Edge-preserving filter techniques (Wang, Y, 1997)
- Region-Based Level Sets (Silveira & Heleno, 2009)
- Markov Random Fields (Pelizzari & Bioucas, 2007)
- Wavelet-based (Niedermeier, 2002)

K-means Cluster (Soares et al., 2012)

(*) D.C. Mason et al., Construction of an intertidal digital elevation model by the water-line method, GRL,1995



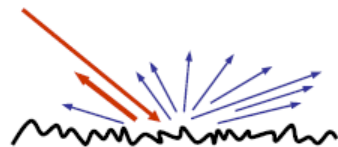
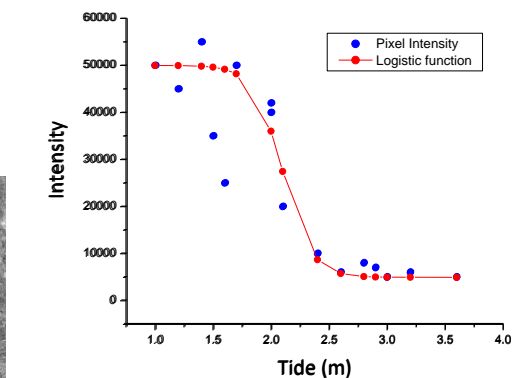
Ciências
ULisboa

Mapping Intertidal morphology

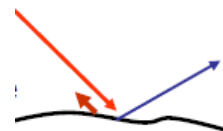
Multitemporal Intensity Logistic Analysis (MILA)



Low tide



Diffuse to Specular scattering



High tide



Mapping Intertidal morphology

Multitemporal logistic analysis

Temporal Variability

> Standard Deviation

$$\sigma_a(x, y) = \sqrt{\frac{1}{M} \sum_{i=1}^M (J_i - \bar{J})^2}$$

$$\sigma(x, y) = \sqrt{\frac{1}{M} \sum_{i=1}^M (10 \cdot \log_{10} J_i)^2 - \left(\frac{1}{M} \sum_{i=1}^M 10 \cdot \log_{10} J_i \right)^2}$$

> Amplitude dispersion

$$D_a = \frac{\sigma_a}{\mu}$$



Mapping Intertidal morphology

Logistic analysis

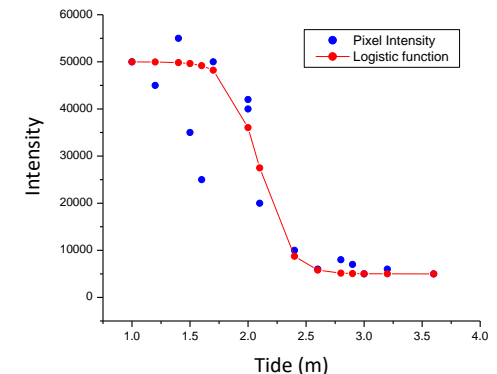
The logistic function relates the height of the resolution cell (h) with the pixel intensity (J_i). The function is defined by the parameters (a , k , h) and is given by:

$$J_i = \frac{k}{1 + e^{-a(h_i - h)}} \quad i = 1, \dots, M$$

In which k is the maximum intensity, a is the steepness of the logistic function ($a = -8$, if negative the function decrease), h is the height of the resolution cell and h_i is the tide height for image i .

$$\min \left\{ \sum_{i=1}^M h_i - h + \frac{1}{a} \ln \left(\frac{J_i}{k - J_i} \right) \right\}^2$$

h and k are the parameters to be estimated



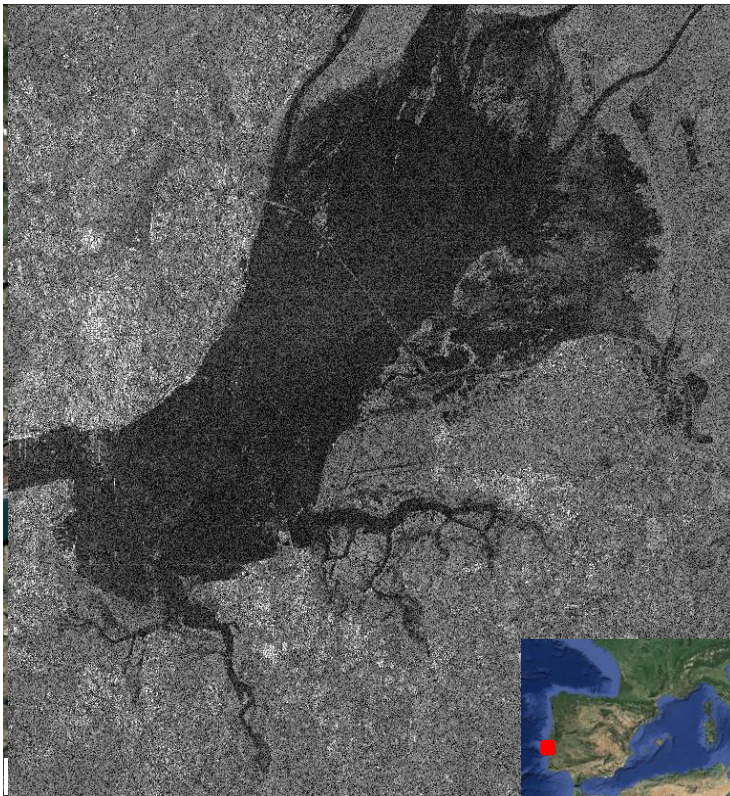
We have to search on the solution space for the values (h , k) that minimize the expression.



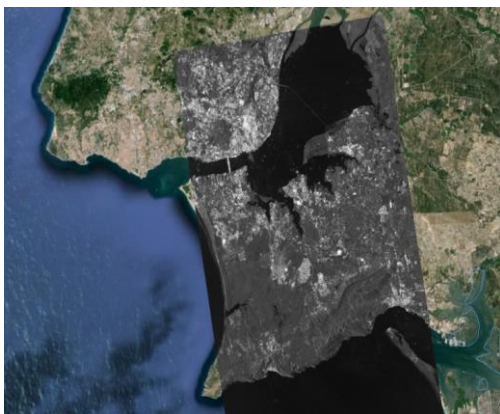
Ciências
ULisboa

Mapping Intertidal morphology

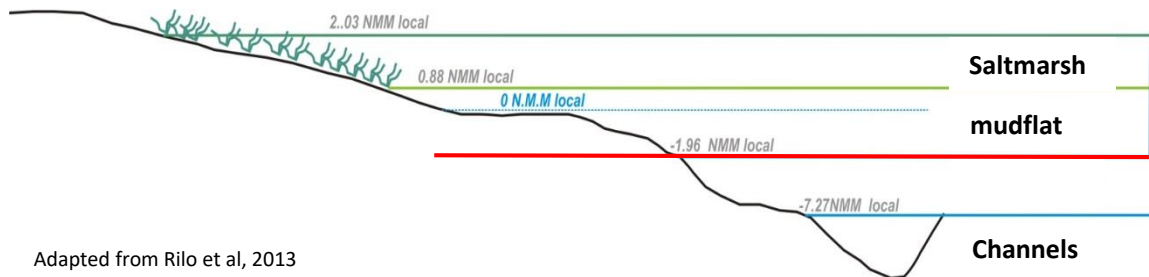
Test Site: Tagus Estuary



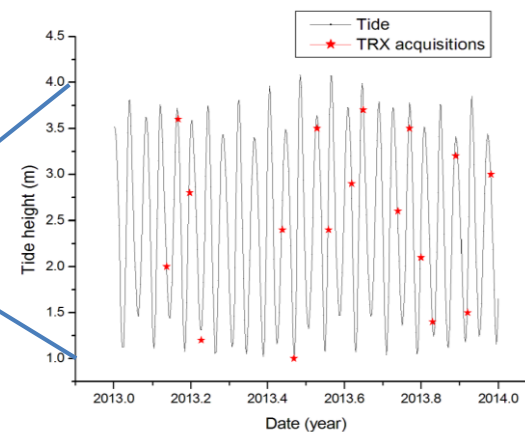
SAR data and Tide height



TerraSAR-X SAR images (19)
 From January 2013, January 2014
 Ascending, HH polarization, 3 m resolution
 Incidence angle: 42.8 degrees
 (Project: DLR COA 1840)



Adapted from Rilo et al, 2013



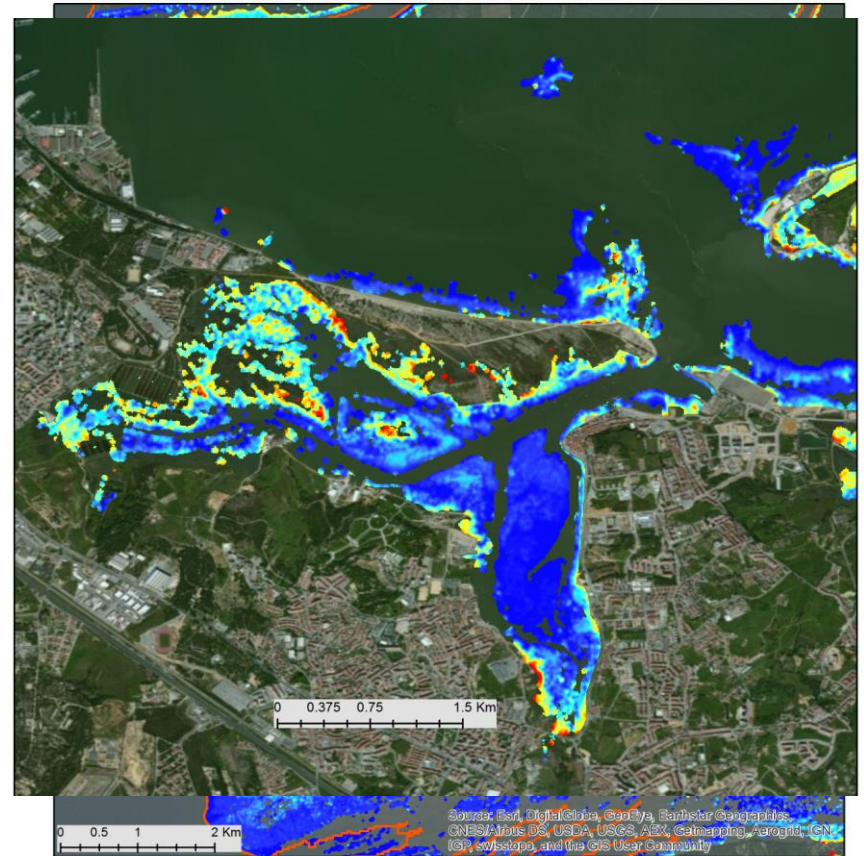
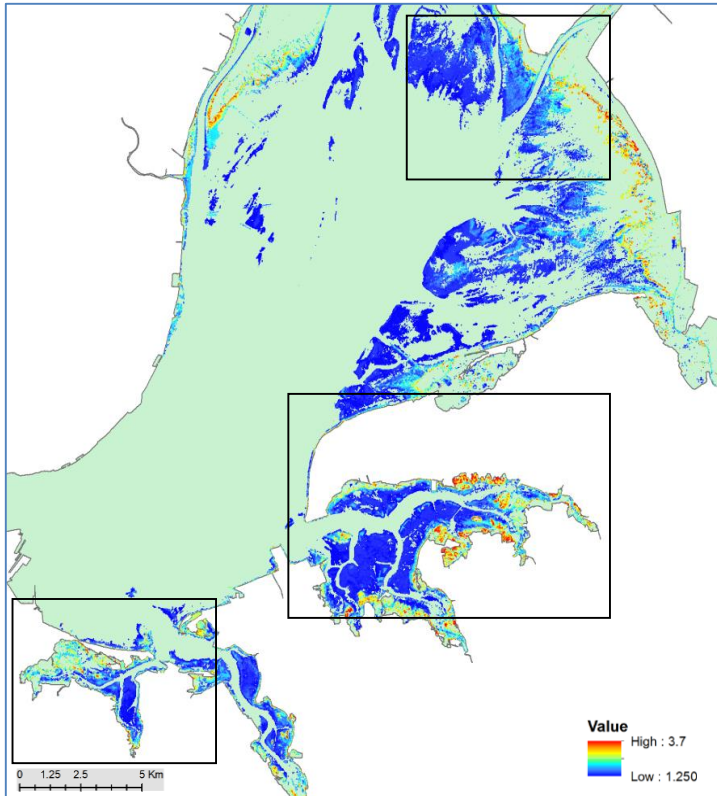
Tagus estuary tide height at 18:30 from 2013, January to 2014, January.



Ciências
ULisboa

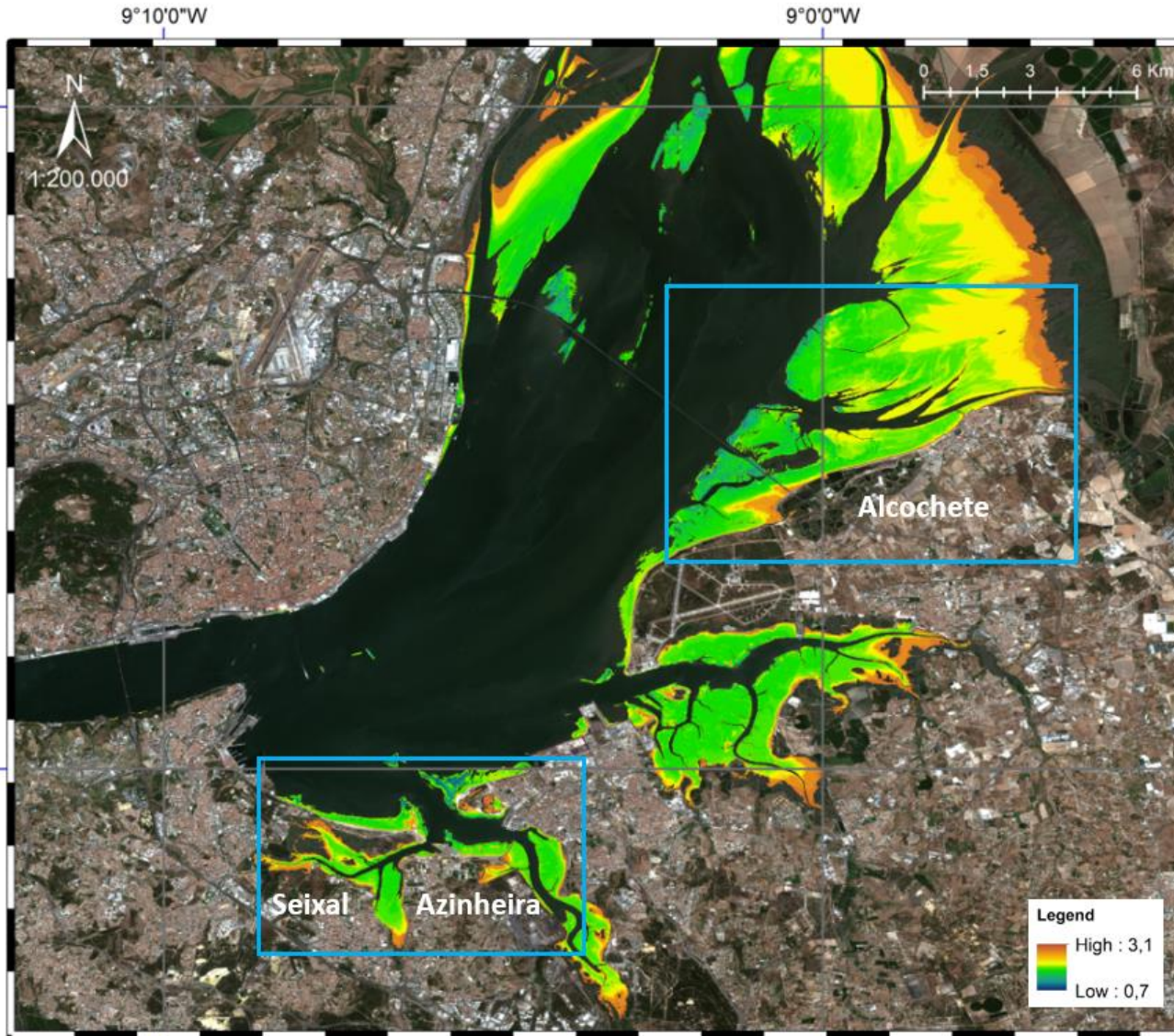
Mapping Intertidal morphology

Intertidal elevation model

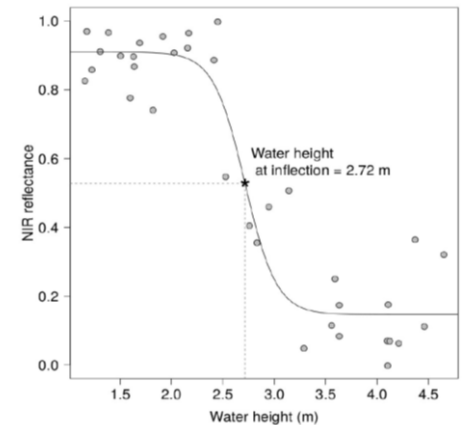




Mapping Intertidal morphology



Sentinel-2 - Tejo



Bué et al., 2020

9°7'30"W

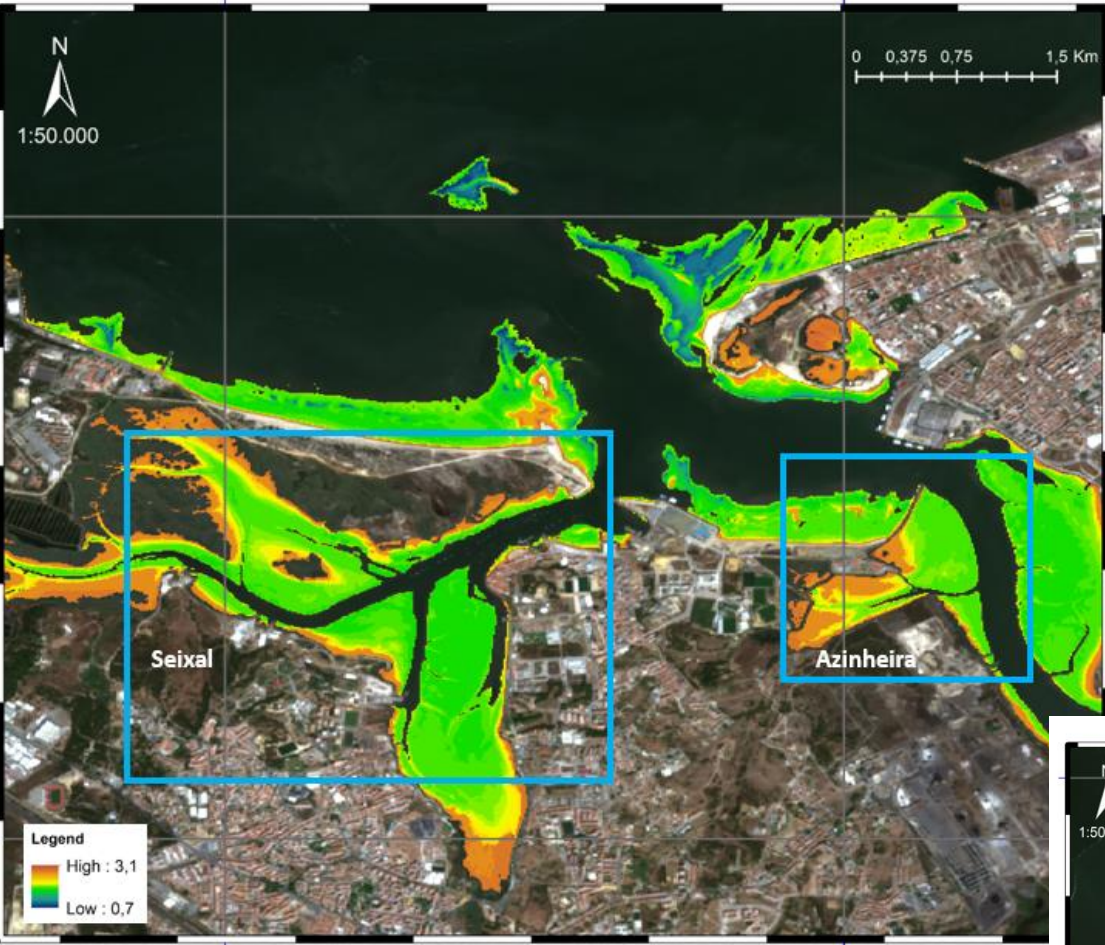
9°5'0"W



1:50.000



38°40'0"N



Seixal

Azinheira



9°0'0"W

8°57'30"W

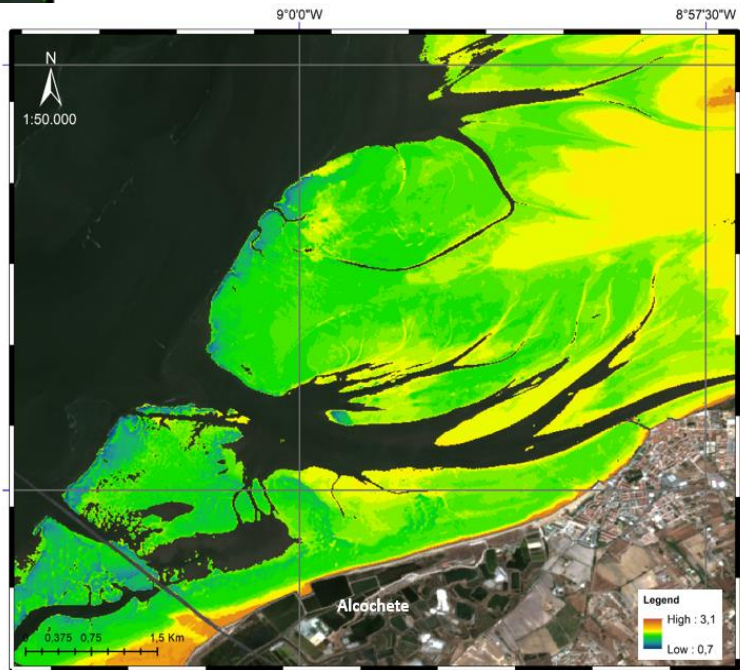


1:50.000



38°47'30"N

38°45'0"N

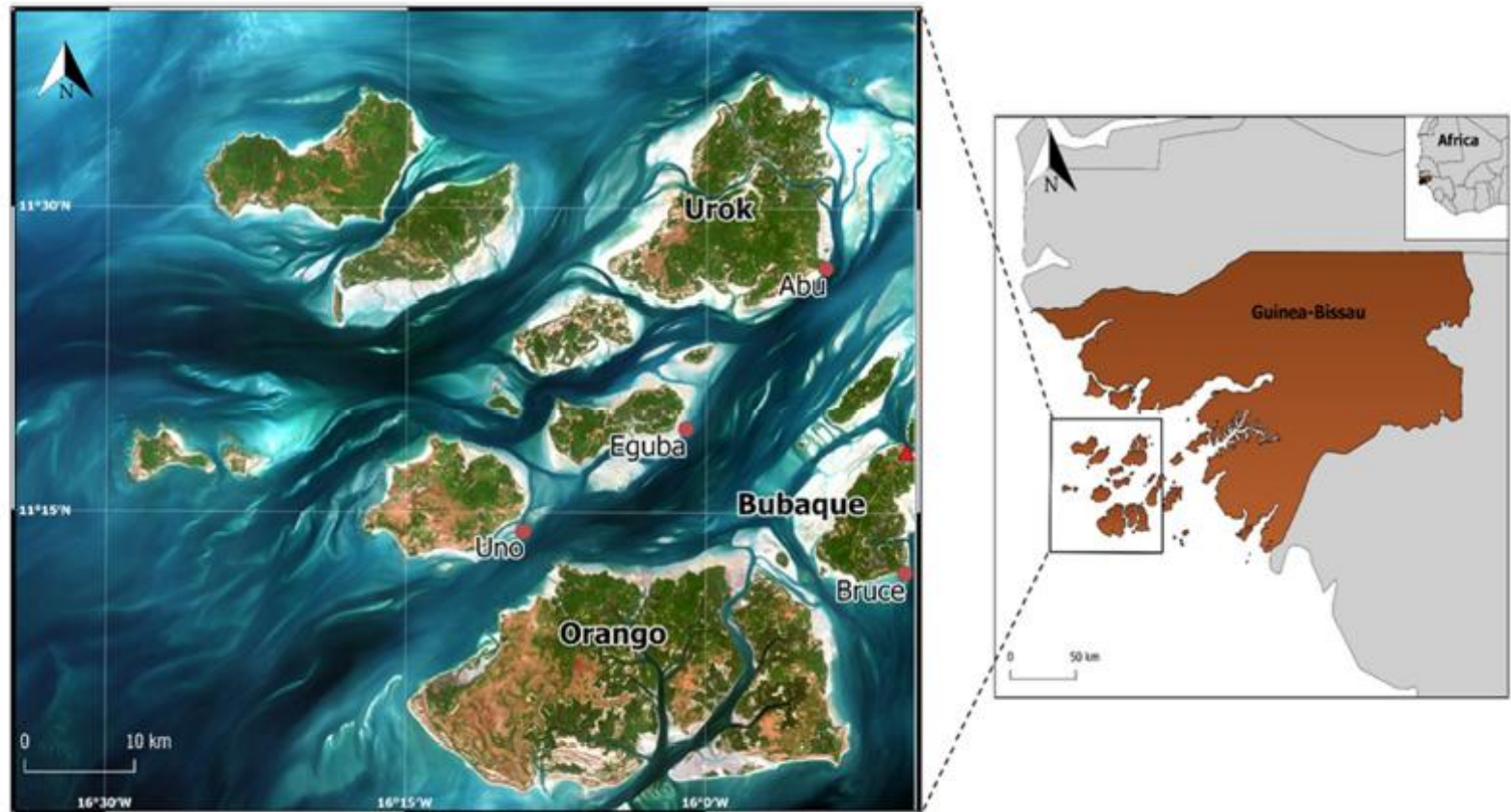


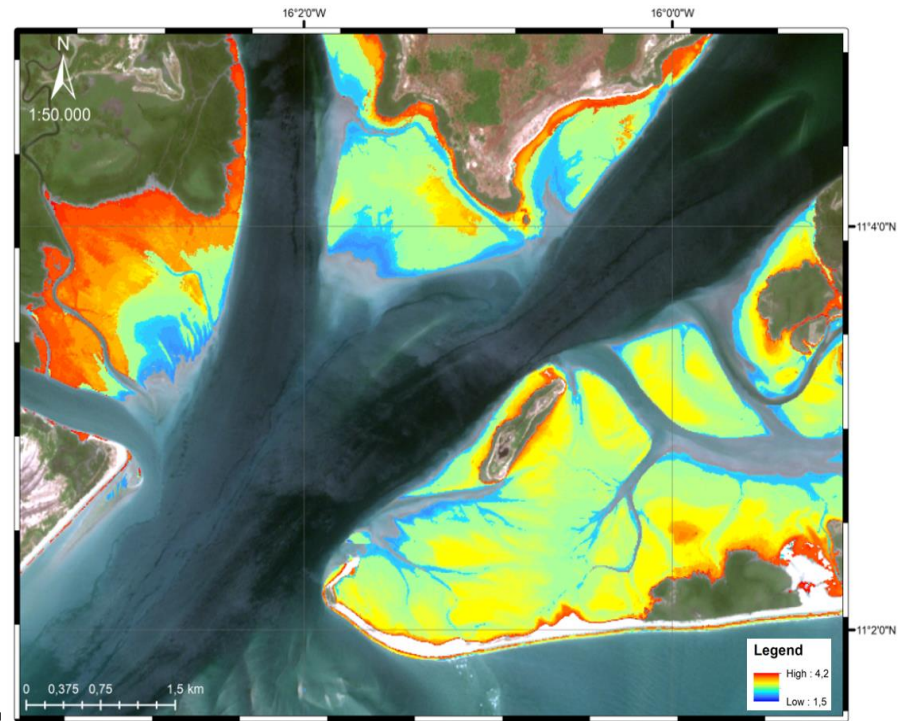
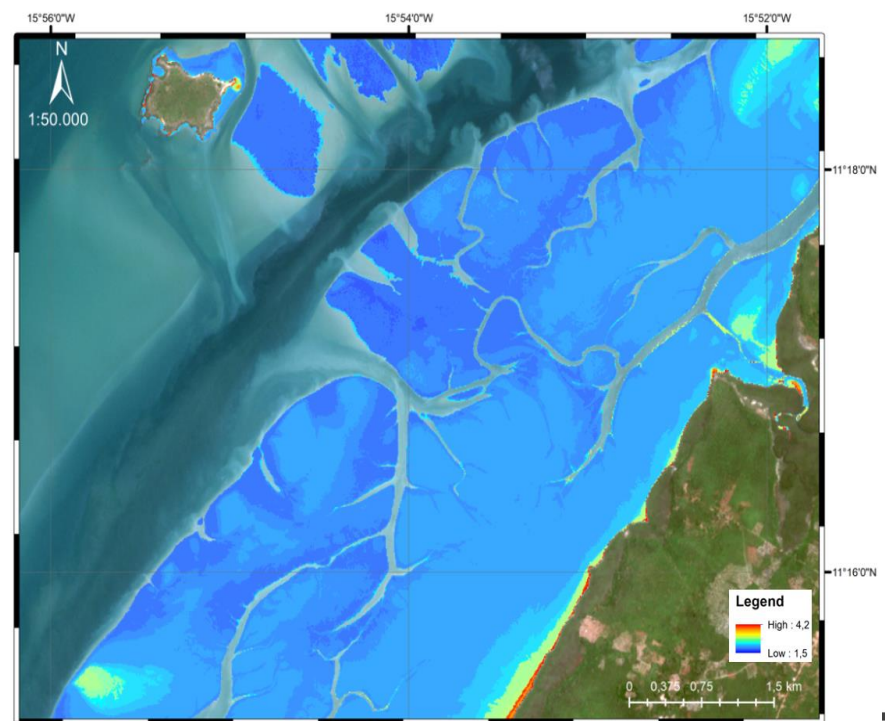
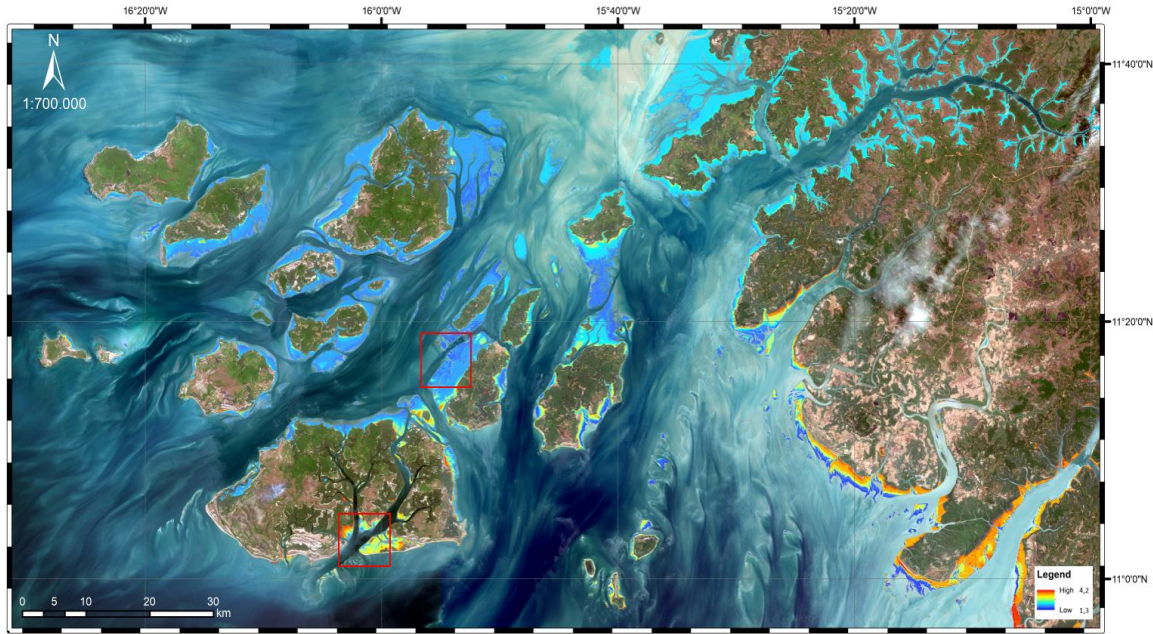
Alcochete



Mapping Intertidal morphology

Sentinel-2 - Bijagós





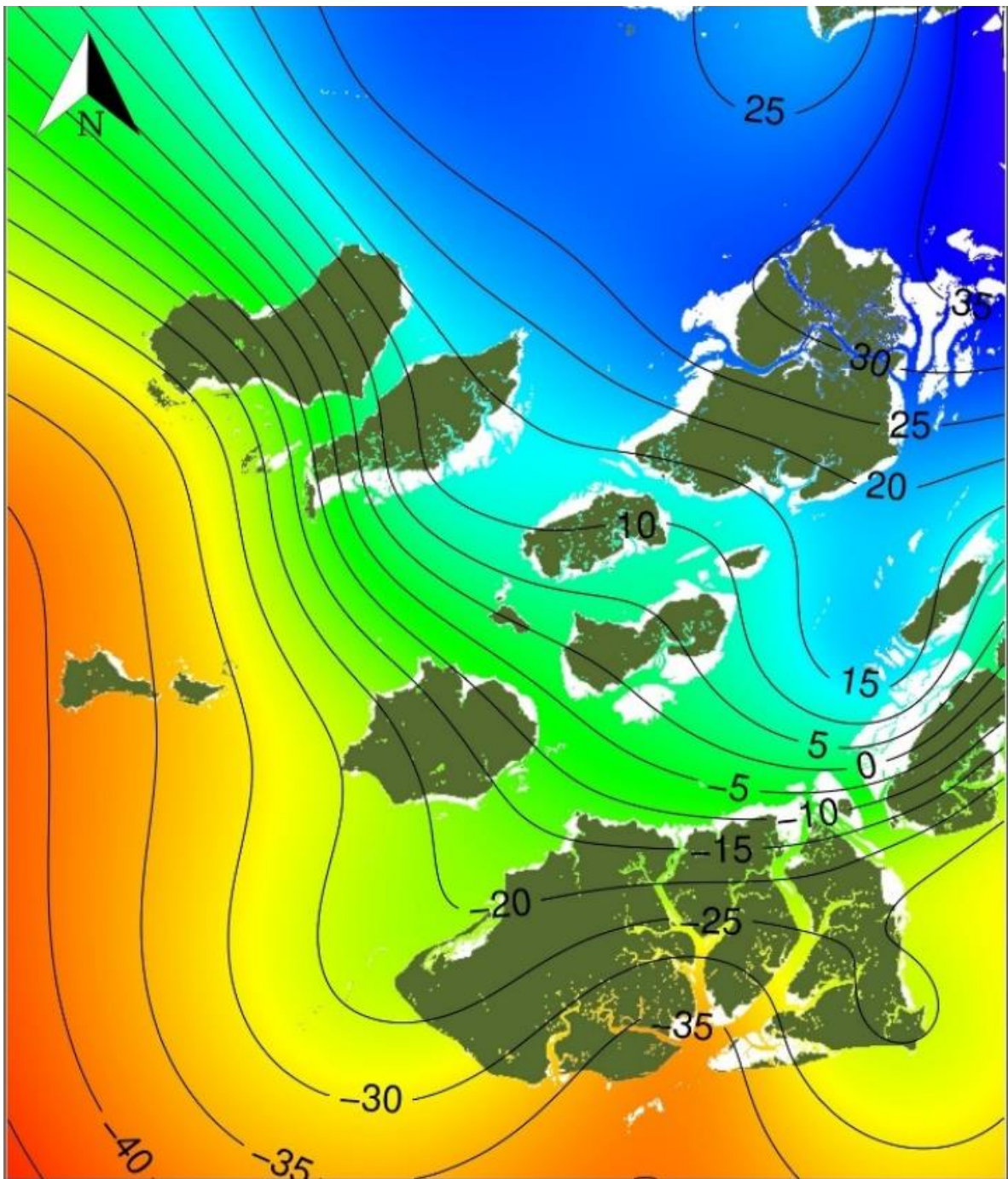


Figure 9. Cotidal lines, showing the time-lag (in min) from the reference point in Bubaque, estimated using data from 50,000 random intertidal pixels as a function of longitude and latitude, using a generalized additive model (GAM) with thin-plate regression splines





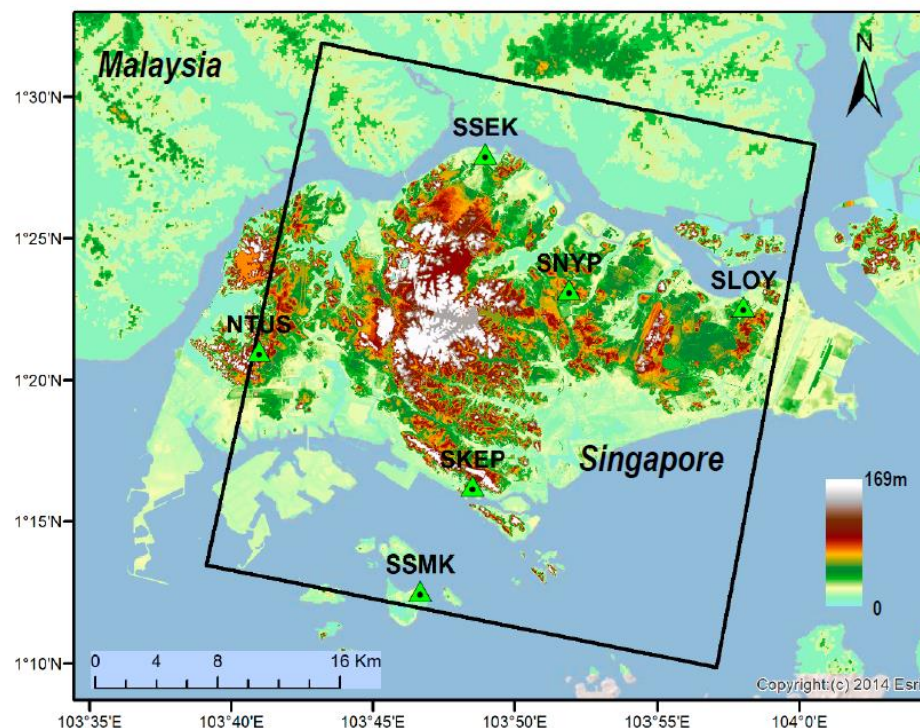
Ideas to develop / Challenges

1. Transfer learning in space and time
2. Unbalanced data classes (parcels)
3. Deep learning - CNN
4. Long short term memory (forecast)
5. Object recognition/segmentation

Article

Insar Maps of Land Subsidence and Sea Level Scenarios to Quantify the Flood Inundation Risk in Coastal Cities: The Case of Singapore

Joao Catalao ^{1,*} , Durairaju Raju ² and Giovanni Nico ^{3,4} 



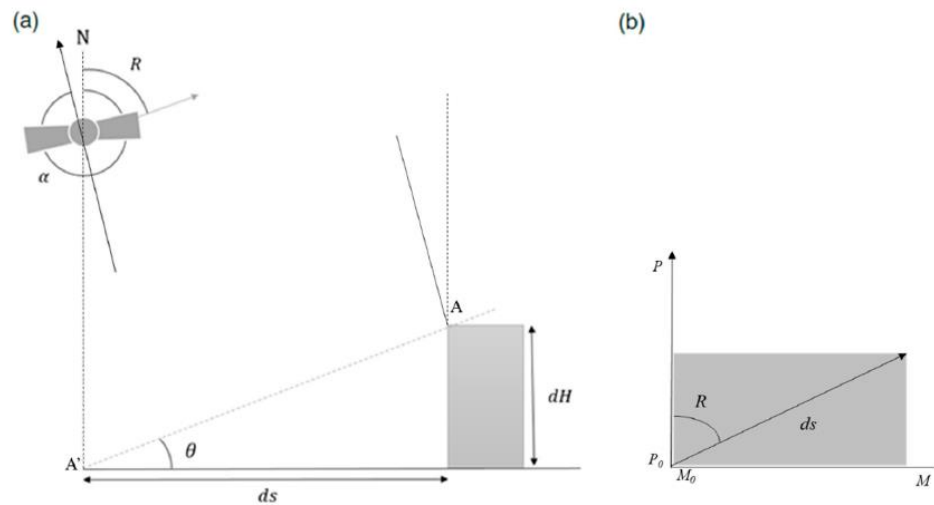
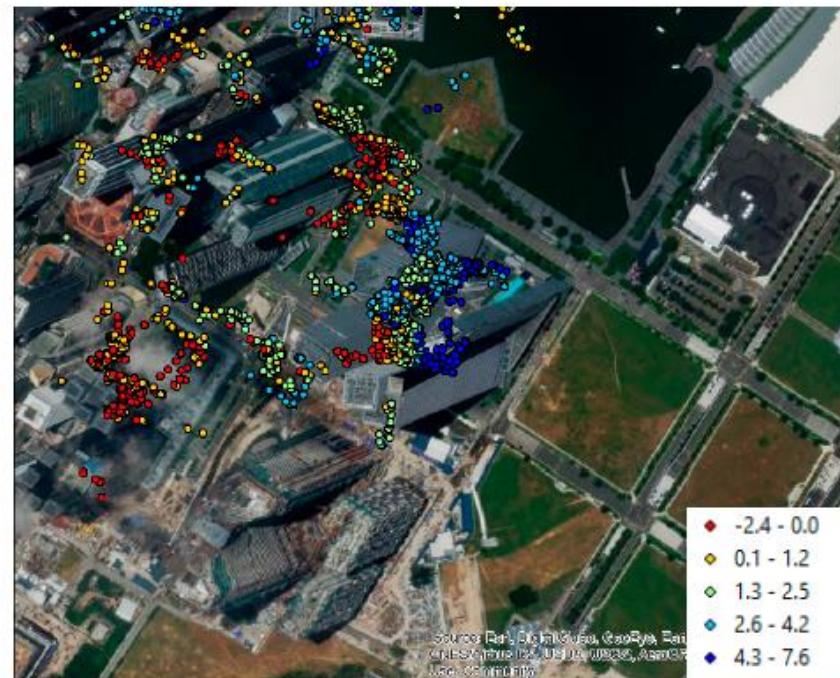
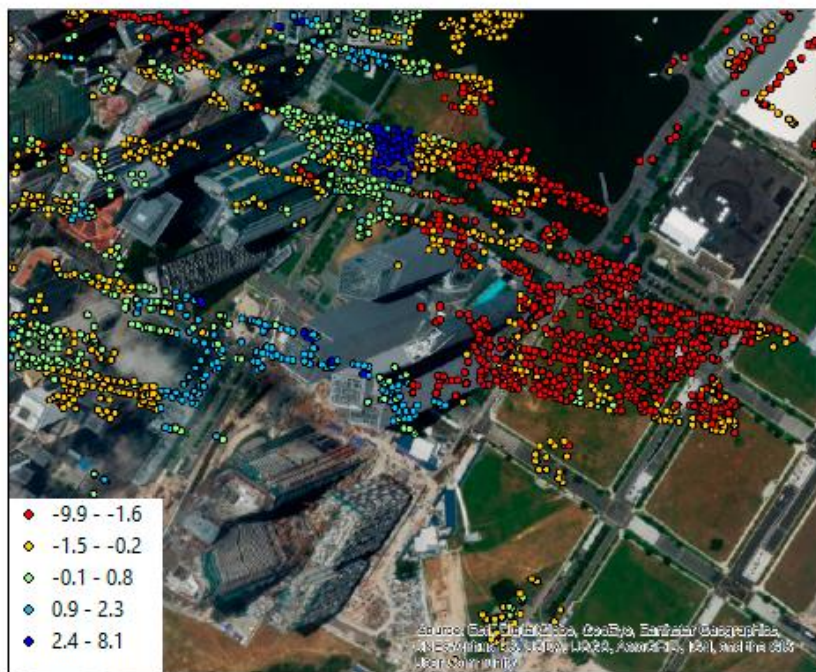


Figure 3. (a) SAR acquisition geometry of a building and (b) planimetric view of the geolocation error.

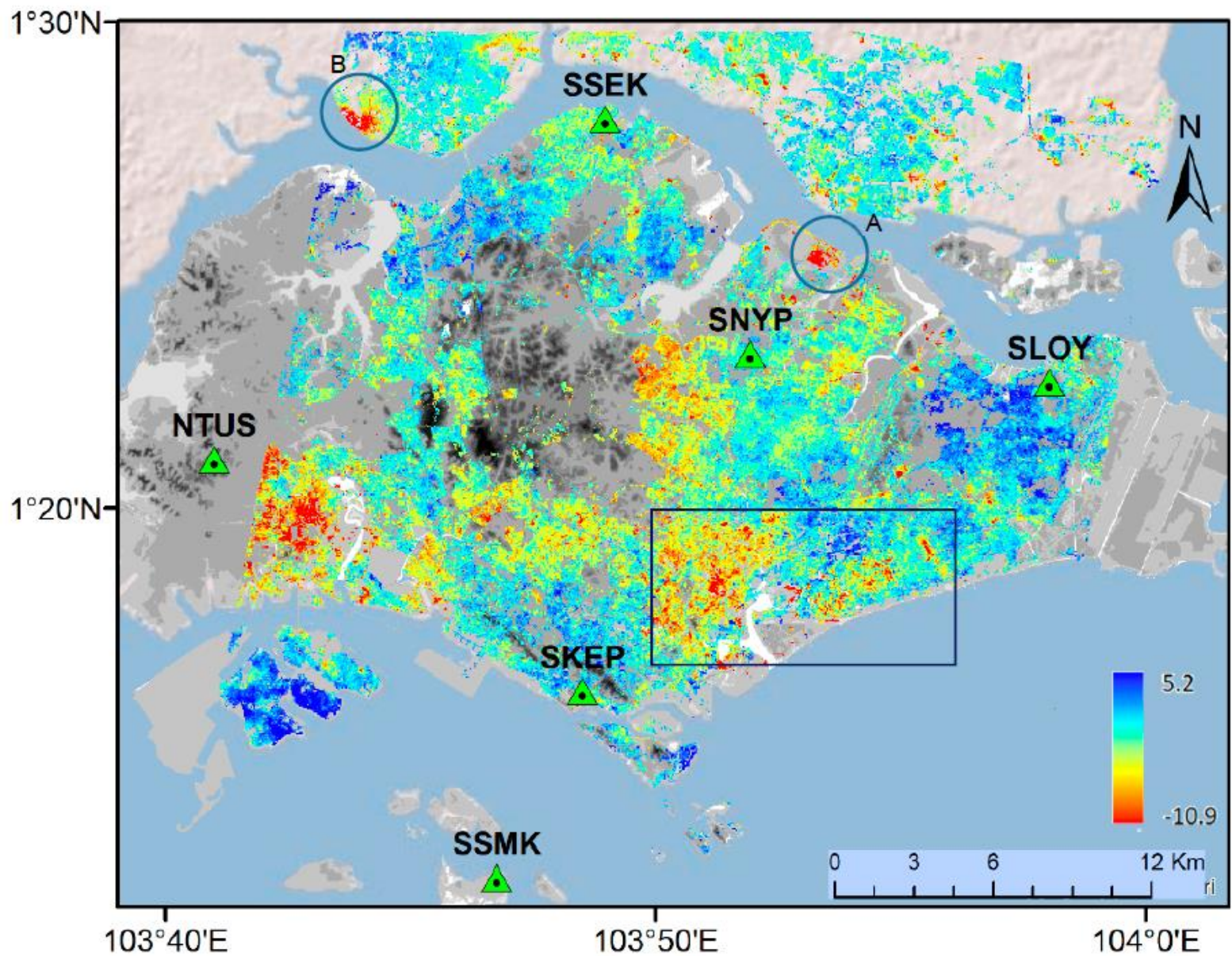


Figure 5. Local land deformation rate between 2011 and 2016 estimated by PSI. Negative rates are referred to subsidence. Deformation rate in mm/yr.

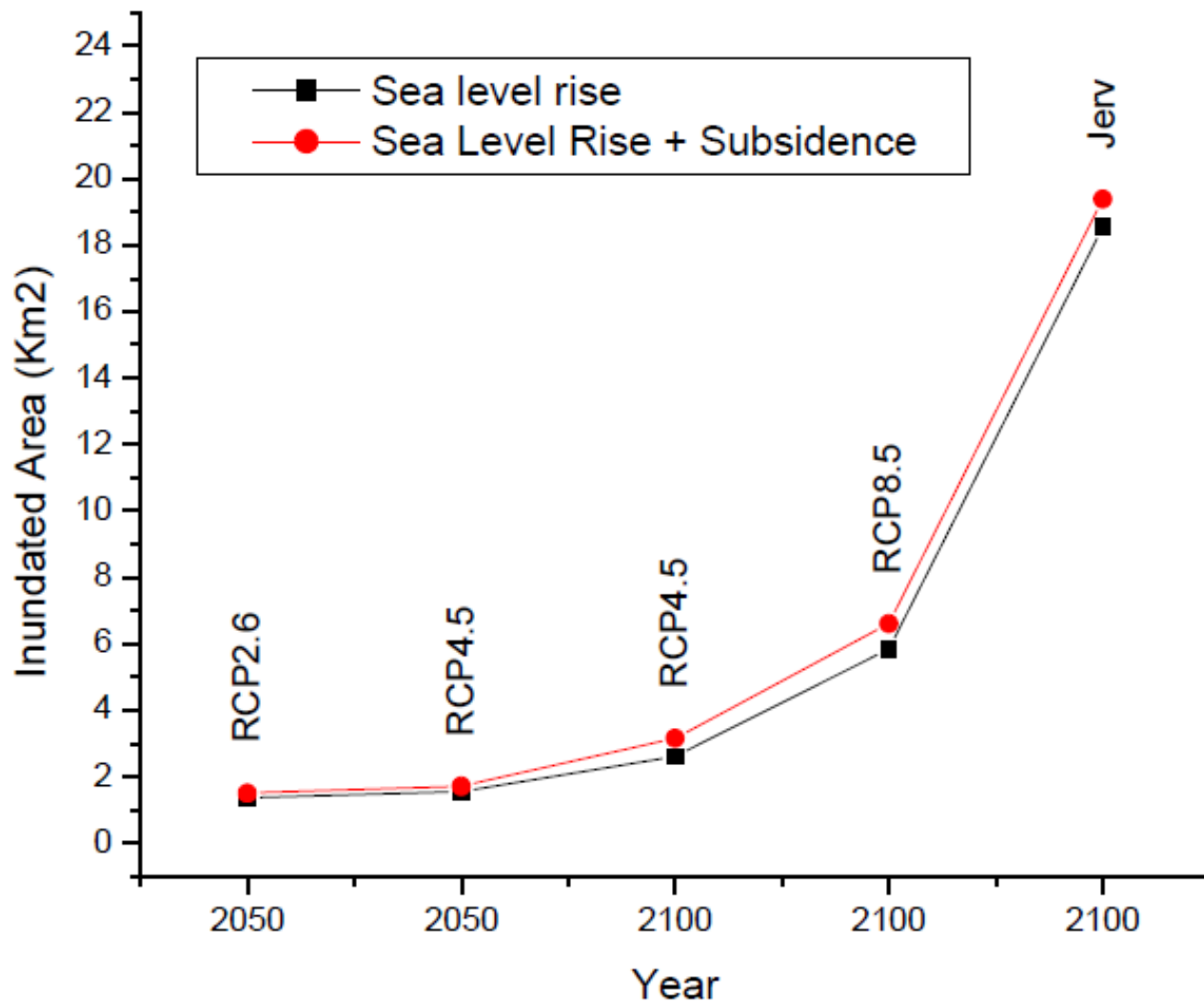
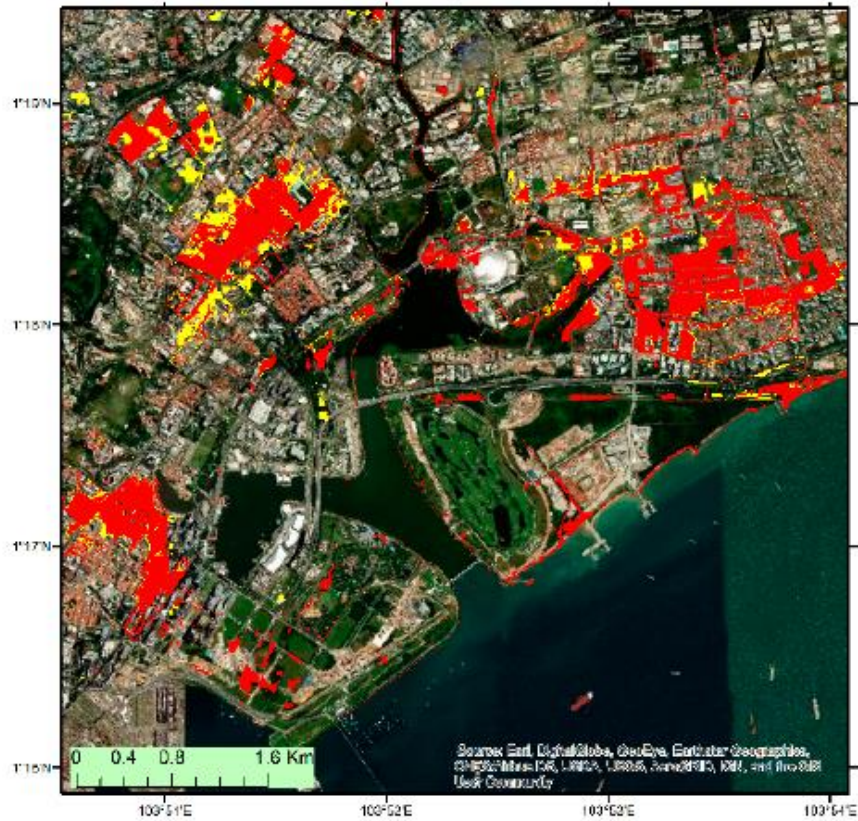


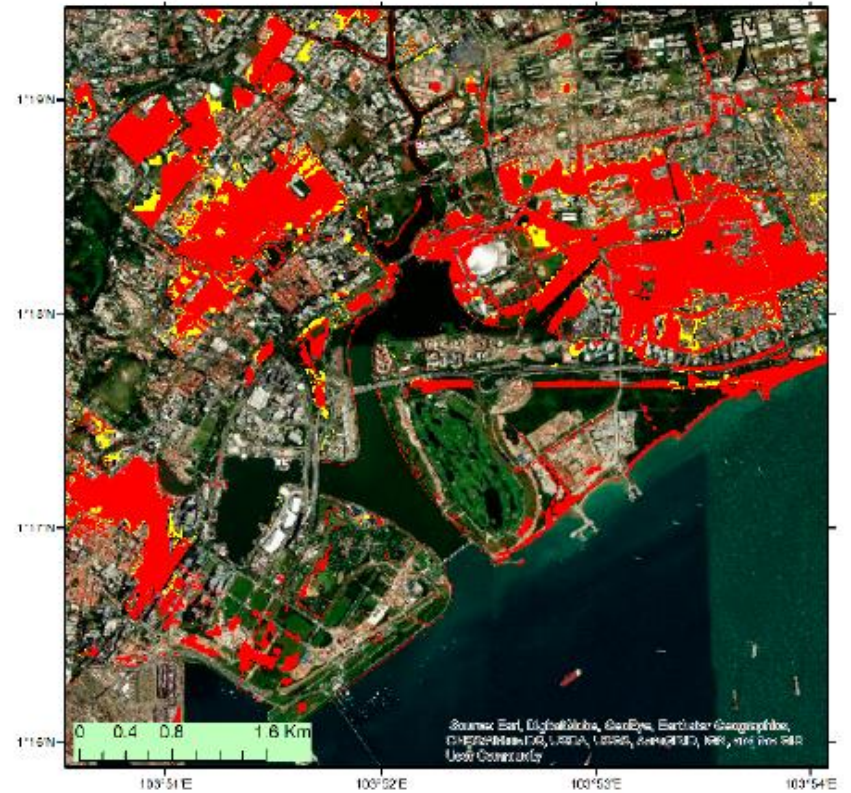
Figure 10. Projected inundated area under different RCP scenarios.

RCP4.5, 2100



(a)

RCP8.5, 2100



(b)

Figure 9. Inundation maps for Singapore downtown under two RCPs scenarios and local land subsidence estimated by SAR interferometry. The effect of sea level rise is shown in red and the combined effect of sea level rise and local land subsidence is shown in yellow. (a) Inundated area under RCP4.5 projection and (b) inundation area under RCP8.5 projection.