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1 **Mangrove zonation mapping in West Africa, at 10-meter**
2 **resolution, optimized for inter-annual monitoring**

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Mangrove zonation mapping in West Africa, at 10-meter resolution, optimized for inter-annual monitoring

The surface area of mangrove ecosystems in Senegal have fluctuated substantially over several decades. Satellite data at 10 to 30-meter resolution, which has been available since the 1980s, has allowed the mapping and quantification of these dynamics. However, the plant formations have reorganized internally; this has not been well-documented, possibly because there is no established method for detecting zonation of the Senegalese mangrove. This paper proposes a two-step method for mapping the zonation of the Saloum Delta mangrove. First, mangrove surfaces were detected using machine learning methods from an object-based time series. Finally, a typology was developed through object-based clustering using time-series metrics derived from the harmonic regression modelling of the vegetation fraction. A comparison with field data allowed us to determine the number of classes and discriminating variables. The results showed that the selected method resulted in an overall accuracy of 97.55% (Kappa = 95.42) for the land cover at 4 classes (Water, Mangrove, Salt flats, Other land covers), with an F1-Score of 98.91% for the mangroves. Second, our results suggest that the annual trend of the vegetation fraction at the object scale is effective in differentiating mangrove zonation into three classes based on canopy density and stand height (HM: High mangrove; LDM: Low and dense mangrove; LOM: Low and open mangrove). Finally, the temporal stability of the classes and uncertainty around the magnitudes of the plant fraction values per class were assessed by Bayesian inference. An overall accuracy of 85.5% can be expected to identify the zonation typology on an inter-annual scale. This mapping technique can be used to characterize the rate of change in zonation in response to environmental changes and to guide management strategies.

29 **Key policy highlights**

30

- 31 • There is currently no method for detecting the zonation of the Senegalese
32 mangrove.
- 33
- 34 • A typology of mangrove zonation was created based on canopy density and
35 stand height.
- 36
- 37 • Analyzed temporal stability/uncertainty by time series synthesis & Bayesian
38 modeling.
- 39
- 40
- 41 • Accurately identified typology (85.5% accuracy) in annual monitoring context
- 42
- 43 • Reduced uncertainty margins for monitoring using temporal segmentation
44 algorithms.
- 45
- 46

47

48 **Keywords:** Mangrove; Sentinel-2; Sentinel-1; Times series; Machine Learning; OBIA

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54 **1. Introduction**

55 Mangrove mapping is an important aspect of ecosystem management strategies (Giri et al.,
56 2011). The availability of remotely sensed megadata at decametric spatial resolution allows the
57 classification of different surface states over large continental areas (Mutanga and Kumar,
58 2019), especially at a scale that can guide local and national environmental policies. Access to
59 and processing of Landsat and Sentinel archives have been facilitated by freely available cloud
60 platforms, such as the Google Earth Engine (GEE) (Alonso et al., 2016; Gorelick et al., 2017;
61 Wang et al., 2019). Furthermore, the computational power allocated by these platforms
62 provides an opportunity for tropical countries to set up complex processing chains with big
63 data (Midekisa et al., 2017). However, their dimensionality remains an important issue with
64 regards to reducing computation times, which decreases the redundancy of information from
65 different sensors (Myint et al., 2011; Hu et al., 2019; Stromann et al., 2020) and ensures
66 classification efficiency (Speiser et al., 2019). Moreover, the Sahelo-Sudanese coastal zone
67 contains socio-ecosystems that generate a variety of landscapes (Temudo et al., 2015; Andrieu,
68 2020) that can be difficult to map (Cabral and Costa, 2017; Asenso Barnieh et al., 2020) and
69 which can cause spectral confusion between the mangrove and dense forests on dry land
70 depending on the season. Therefore, extracting the most effective data and variables is essential
71 (Schulz et al., 2021).

72 Mangrove forests cover large areas (Cabral and Costa, 2017; Andrieu, 2018) and provide
73 various ecosystem services (Cormier-Salem, 1999; Walters et al., 2008; Mukherjee et al., 2014;
74 Arumugam et al., 2021). Global issues of climate change mitigation through carbon
75 sequestration and preservation of mangrove biodiversity must be considered alongside local
76 issues such as access to resources (Cormier-Salem et Panfili, 2016). Monitoring mangrove
77 dynamics on a regular basis could help better reconcile resource management within changing
78 environments.

79 Mapping mangrove ecosystems in West Africa is crucial for developing effective
80 ecosystem management strategies (Jia et al., 2018). With the help of high resolution satellite
81 data from Landsat and Sentinel, as well as access to cloud platforms such as Google Earth
82 Engine (GEE) (Alonso et al., 2016; Gorelick et al., 2017; Wang et al., 2019), it is now possible
83 to use powerful computing resources and advanced processing methods to better understand
84 the dynamics of mangroves in this region (Midekisa et al., 2017). These methods allow for the
85 management of long and dense time series data, which can provide a comprehensive view of
86 mangrove ecosystems. The mapping of mangroves in West Africa is particularly valuable due
87 to the numerous ecosystem services they provide (Cormier-Salem, 1999; Walters et al., 2008;
88 Mukherjee et al., 2014; Arumugam et al., 2021).

89 Although databases of mangrove areas exist (GWM, 2010; USGS, 2014), they are
90 highly inaccurate, particularly in West Africa due to persistent cloud cover (Bunting et al.,
91 2018). The authors also mention that fringing and fragmented mangroves are sometimes
92 omitted, even though they are frequently encountered in West-Africa (Liu et al., 2021).
93 Mapping the extent of mangroves has been the subject of many studies (Kuenzer et al., 2011;
94 Wang et al., 2019), and various mapping methods have been developed to produce local data.
95 SPOT data has successfully mapped the extent of mangroves in West Africa over several years
96 with an object-based image analysis (OBIA) approach (Conchedda et al., 2008). Landsat data
97 has also led to the production of accurate maps using a pixel approach combined with linear
98 spectral unmixing (Han et al., 2018). These data are also advantageous due to the long time

99 series. Cloud cover has often been mentioned as an impediment to mapping mangroves in the
100 tropics with passive sensors (Kuenzer et al., 2011); active sensors are therefore of interest for
101 mapping mangrove surfaces. These data also present good precision scores, especially with
102 OBIA approaches (Flores de Santiago et al., 2013), and most of these methods are fairly
103 accurate, particularly with Sentinel-2 optical data (Mondal et al., 2019) and Sentinel-1 and 2
104 radar-optical combinations (Liu et al., 2021). These data have the advantage of being freely
105 accessible and easily available on GEE. Machine learning approaches, which typically combine
106 a large volume of data to avoid the biases of single-date image-based mapping (Cardenas et
107 al., 2017), are currently favored for map development (Chen et al., 2017; Mondal et al., 2019;
108 Liu et al., 2021; Wang et al., 2018). Several studies have highlighted the contributions of cloud
109 solutions, such as GEE, for processing time series and multi-source data (Cardenas et al., 2017;
110 Chen et al., 2017; Liu et al., 2021; Xiao et al., 2021). Combining optical (Landat-8 and
111 Sentinel-2) and radar (Sentinel-1) data was found to improve the discrimination of Land Use
112 Land Cover and mangrove classes (Clerici et al., 2017; Zhao and Qin, 2020; Xiao et al., 2021).
113 Decision trees, such as Classification And Regression Trees (CART) or Random Forests (RF)
114 are commonly used for mangroves (Giri et al., 2015; Zhang et al., 2017; Mondal et al., 2019;
115 Thomas et al., 2018; Chen et al., 2020; Xiao et al., 2021). Liu et al. (2021) combined three
116 algorithms with a gradient boosting machine (GBM) and neural network (NN) to form a
117 powerful machine learning package. They achieved accuracy scores above 95% using S2 and
118 S1 images in West Africa, and developed the most accurate mapping for this area to date.

119 Although the available mapping of mangrove areas seems reliable, differentiating
120 between the mangrove plant formations using optical and radar data is challenging in West
121 Africa (Flores de Santiago et al., 2013). Indeed, these can be characterized by the coverage and
122 stand height, and by estimating the specific species compositions. Thus, plant formations
123 roughly represent the zonation of mangroves and the resultant spatial organization of
124 population dynamics at the local scale.

125 Subdivision of mangroves into several facies at a decametric resolution is a complex
126 process; although it has been performed in other mangrove areas, it has rarely been attempted
127 in Senegal. Various approaches have been developed to subdivide mangroves. The OBIA
128 method consistently achieves good scores (Wang et al., 2019). Myint et al. (2008) mapped
129 mangroves at a specific level using Landsat images with an overall accuracy of 94.2% and a
130 kappa coefficient of 0.91; the pixel classifiers had an overall accuracy of 62.8% and a kappa
131 coefficient of 0.57. Wang et al. (2018) achieved an overall accuracy of 70.95% for species
132 community discrimination using S2 images with a combination of the object approach and an
133 Random Forest (RF) classifier. In addition, approaches using pixel-level mangrove phenology
134 have been used to classify mangroves at specific levels (Bullock et al., 2017; Valderrama-
135 Landeros et al., 2021). Vegetation indices from dense S2 time series also made it possible to
136 classify mangroves according to a three-class typology (*Rhizophora mangle* fringe, basin, and
137 *Avicennia germinans* shrub) with overall accuracy scores between 92 and 95% (Vizcaya-
138 Martínez et al. 2022). The authors were able to map the evolution of this typology after
139 disturbances and measured species recovery, which are similar to those of the mangroves in
140 Senegal. Finally, linear spectral unmixing consistently shows good results for quantifying
141 mangrove canopy cover (Monsef and Smith, 2017; Bullock et al., 2020; Lymburner et al.,
142 2020) and for establishing a forest composition typology (Gudex-Cross et al., 2017). For
143 example, linear spectral unmixing was used to establish a 3-class typology in Australia
144 (woodland, open forest, closed forest) based on the mangrove cover rate from Global Mangrove

145 Watch (GMW) data (Lymburner et al., 2020). Finally, several studies have used RADAR data
146 to map mangrove species (Flores de Santiago et al., 2013; Ghazali et Wikantika, 2021).
147 Although RADAR data has shown good accuracy in discriminating mangrove, the species
148 classification remains more delicate and obtains low (OA = 26%) to moderate (OA ≈ 65%)
149 scores. The best scores were obtained by optimizing the scale parameter with an OBIA
150 approach (Flores de Santiago et al., 2013) or by deriving a dual-polarity RADAR vegetation
151 index (DpRVI) with Sentinel-1 (Ghazali et Wikantika, 2021).

152 Furthermore, significant fluctuation in mangrove forest area in West Africa has
153 occurred in recent decades (Andrieu, 2018). Mangroves in Senegal have experienced surface
154 regeneration since the mid-1990s (Conchedda et al., 2011; Dièye et al., 2013; Andrieu, 2018;
155 Fent et al., 2019; Lombard and Andrieu, 2021). However, the respective shares of species in
156 regeneration processes differ according to the hydrosystems (Andrieu et al., 2020; Lombard et
157 al., 2020). Therefore, a map of plant formation is important to obtain an overview of mangrove
158 composition and to understand mangrove resilience to environmental changes. Plant
159 formations can estimate the specific composition of the environment, the density of the cover,
160 and the size of the individuals making up the group. Moreover, as was pointed out by Wang et
161 al. (2019), mapping mangrove communities is important for conservation strategies (Jia et al.,
162 2018). We assume that fine-scale processes participate in the spatial organization of mangrove
163 zonation. The establishment of propagules of different species is constrained by environmental
164 variables such as salinity and hydroperiod (Krauss et al., 2008) or sedimentary processes (Balke
165 et al., 2013). In addition, propagule establishment has been reorganized in the face of recent
166 environmental fluctuations in Senegal (Lombard et al., 2020). Therefore, our objective is to be
167 able to map mangrove zonation, leading to an understanding of the arrangement of species
168 zonation resulting from reproduction and growth, which are processes sensitive to
169 environmental fluctuations. Therefore, our objective was to develop an optimized and robust
170 multilevel mapping method for mangrove plant formations in the Sahelo-Sudanese delta.

171

172 By utilizing the knowledge gained from the different approaches mentioned above, we
173 developed a method for mapping mangroves at two levels. First, mangrove surfaces were
174 detected by machine learning of objects and corrected by classification based on linear spectral
175 unmixing. Second, linear spectral unmixing was reapplied to subdivide the mangroves into
176 several plant formations using the OBIA method and classified based on a 1-year time series.

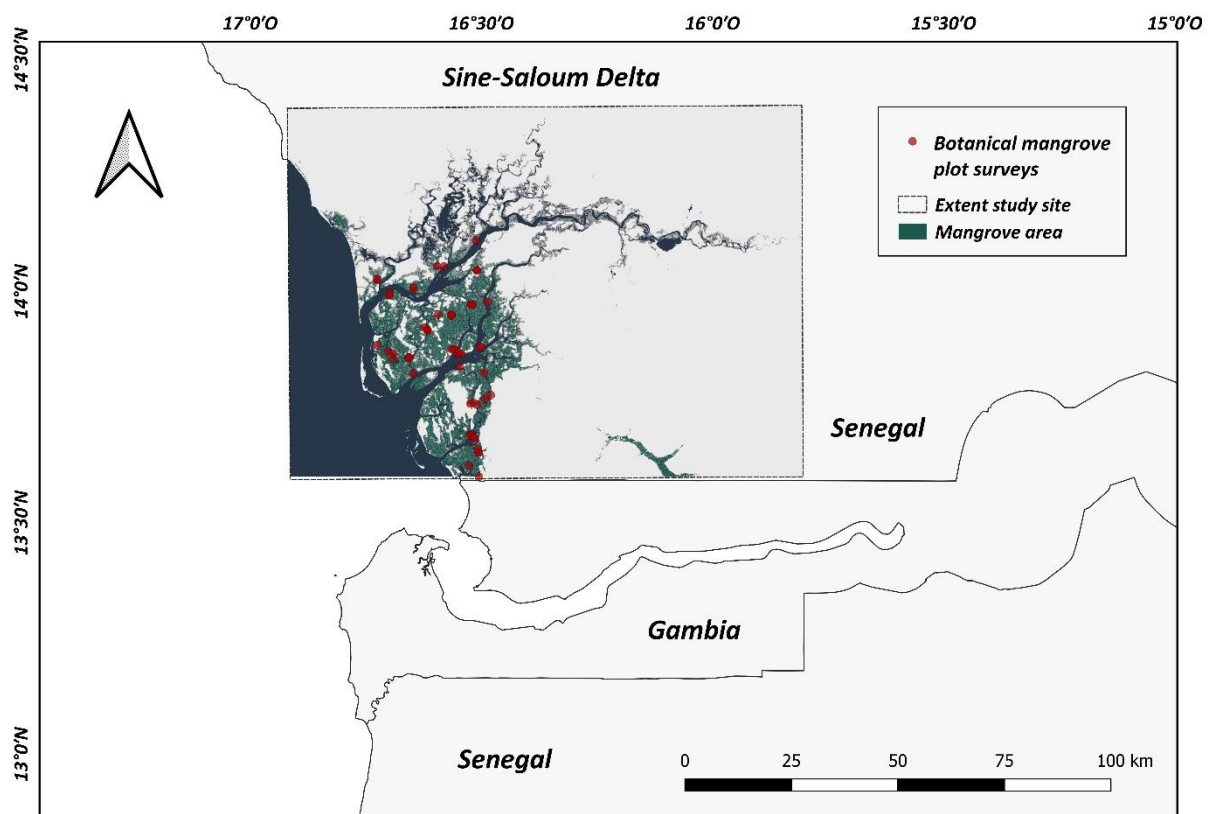
177 **2. Study areas and data**

178 **2.1. Study site**

179 The study area (Fig. 1) covers the Saloum Delta hydrosystem. Located in the Sahelo-Sudanian
180 domain, the north-south gradient is characterized by important inter-annual rainfall variations
181 (Nicholson, 2013; Descroix et al., 2015); mangroves develop under a rainfall of 560 mm in the
182 north and 800 mm in the south (Lombard et al., 2020). The forest comprises six species
183 (*Avicennia germinans*, *Conocarpus erectus*, *Laguncularia racemosa*, *Rhizophora racemosa*,
184 *Rhizophora mangle*, *Rhizophora harissonii*) but three dominate almost the mangrove forest:
185 *Rhizophora racemosa*, *Rhizophora mangle*, and *Avicennia germinans* (Sow et al., 1991; Ndour
186 et al., 2012; Andrieu et al., 2020; Lombard et al., 2020). Species composition, in addition to
187 vegetation cover and tree height, is spatially structured in zonation, and can be subdivided into
188 plant formations. Mangroves in Senegal and Guinea-Bissau have the same zonation patterns

189 (Sow et al., 1991), but the studied hydrosystem showed unique features. In the Saloum Delta
 190 (and the Casamance Estuary), the salinity increases from downstream to upstream (Barousseau
 191 et al., 1985; Descroix et al., 2020), whereas the estuaries of Gambia and those located in
 192 Guinea-Bissau, for example, have a river input and upstream salinity levels closer to those of
 193 fresh water. For Saloum, this results in hypersalinity of the water even after the rainy season
 194 (Diop, 1997). The salinity of the water throughout the Saloum Delta was higher than that of
 195 the sea. For example, in Sine-Saloum in June, salinity is approximately 35‰ at the mouth of
 196 the delta and up to 100‰ in Fatick (82 km from the mouth) (Descroix, 2018). Mangrove
 197 ecosystems in coastal areas are affected by their interplay of soil, topography, and salinity,
 198 which bring complexity to the fine scale. (Marius, 1985; Diop, 1990). In such an ecological
 199 context, the vegetation shows two gradients, north–south and east–west, where the density and
 200 height of the stands differ without changing the specific composition. This makes detecting
 201 species and plant formations within the Saloum Delta challenging. Therefore, sixty fields
 202 surveys were conducted (Figure 1). Using transects following the protocol developed by
 203 Andrieu et al. (2020), the density of the vegetation cover, height of individuals, and rate of
 204 cover of each species were inventoried, which facilitated the evaluation of vegetation formation
 205 maps.

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 209 **Figure 1:** Extent study site and field-based inventory for mangrove zonation.
 210 Sixty botanical surveys were performed and detailed the species, the extent of their relative abundance, and the
 211 height of the vegetation community.
 212

213 *2.2.Data collection and pre-processing*

214 Sentinel-1 and Sentinel-2 images were selected for this study (Table 1). These data have
 215 been proven to be effective for mangrove mapping (Wang et al., 2018; Mondal et al., 2019;
 216 Wang et al., 2019; Jia et al., 2021; Lu and Wang, 2021; Lui et al., 2021; Xiao et al., 2021). The
 217 Sentinel-2 Level-2A data is available through Google Earth Engine. This product offers
 218 orthorectified Bottom-Of-Atmosphere (BOA) reflectances for all 12 bands in a 16-bit unsigned
 219 integer format that has been scaled by a factor of 10,000. We selected all available images (n
 220 = 79) from both sensors between 01/05/2020 and 01/06/2021 on the GEE platform. For
 221 Sentinel-2, the images were filtered with a value of 20% cloud cover. All processing of the S2
 222 time series was performed on the unmasked pixels using ‘QA60’ quality layers. The range of
 223 the number of clear observations is from 47 to 65 cloud-free dates (Table 2). All spectral bands
 224 at 10 m and 20 m resolution of the Sentinel-2 sensor were retained. Bands at 20m were
 225 resampled at 10m. B1 and B9 were not included because they depict atmospheric traits, like
 226 aerosols, water vapor, and cirrus clouds, rather than reflecting surface characteristics of land-
 227 based features. The annual median was calculated for the optical spectral bands.

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Table 1: Characteristics of Sentinel-1 and Sentinel-2 data

Sensor	Processing Levels	Acquisition Period	Relative orbit	Tiles
Sentinel 1	Level - GRD	01/05/2020 - 01/06/2021 (33 scenes)	133	-
Sentinel 2	Level – 2A	01/05/2020 - 01/06/2021 (79 scenes)	-	T28PBA, T28PCA, T28 PCAB, T28PBB, T28PDA, T28PDB

232
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Table : The dates of observation for Sentinel-2 pixels that cloud-free are presented. These dates may differ for each pixel, and the dates shown depict those pixels with the minimum and maximum number of cloud-free days within the analyzed region

Year	Month	Days	Days
		(65 cloud-free dates)	47 cloud-free dates
2020	May	02, 07, 12, 17, 22, 27	02, 12, 17, 22, 27
	June	11, 16, 21, 26	11, 16, 21, 26
	July	01, 06, 21, 26, 31	01, 21
	August	05, 15, 20, 25, 30	15, 25
	September	09, 19, 24, 29	19, 24, 29
	October	04, 09, 14, 19, 24, 29	09, 14, 19, 24, 29
	November	08, 13, 18, 23, 28	08, 13, 18, 28
	December	03, 08, 13, 28	03, 08, 13, 28
2021	January	02, 07, 12, 27	02, 07, 27
	February	01, 06, 11, 16, 21, 26	21, 26
	March	08, 13, 18, 23, 28	03, 08, 13, 18, 28

April	02, 07, 12, 17, 22, 27	02, 07, 12, 17
May	02, 07, 12, 22, 27	07, 12, 22, 27

235

236 Four spectral indices were calculated. The normalized differential vegetation index
 237 (NDVI; Rouse et al., 1974) measures the active photosynthesis of vegetation using reflectance
 238 differences in the red and near-infrared wavelengths; it can be used to distinguish vegetation
 239 from other types of land cover. The near infrared surface water index (NDWI, McFeeters,
 240 1996) measures the amount of water present on the surface of soils using reflectance
 241 differences in the near-infrared and mid-infrared wavelengths; it can be used to detect flooded
 242 areas and to distinguish mangroves from drier vegetation types (Gupta et al, 2018). The
 243 normalized difference moisture index (NDMI, Gao 1996), in particular the DBSI (Dry and Wet
 244 Soil Index) was designed to specifically identify bare areas in dry climates, according to Rasul
 245 et al. (2018). They were selected to identify the wet and dry areas constituting the sometimes
 246 semi-arid landscapes of the study area. The previously mentioned indices (NDVI, NDMI,
 247 NDWI, and DBSI) were used to calculate the GLCM textural indices introduced by Haralick
 248 et al. in 1973. Finally, time-series variables were used to complement reflectance and spectral
 249 indexes dataset. The phase and amplitude of the harmonic model (Clinton, 2016) were
 250 extracted from the annual time series of four spectral indices in the GEE.

251 The Sentinel-1 satellite imagery in the Earth Engine 'COPERNICUS/S1_GRD' image
 252 collection consists of Level-1 Ground Range Detected (GRD) scenes that have been processed
 253 to calculate the backscatter coefficient (σ^0) in decibels (dB). The backscatter coefficient is a
 254 measure of how much microwave radiation is scattered back to the radar sensor by the target
 255 area and is expressed as the target backscattering area (radar cross-section) per unit of ground
 256 area. Since it can vary significantly, it is converted to dB by $10 \cdot \log_{10} \sigma^0$. The backscatter
 257 coefficient can be used to determine physical characteristics of the terrain, including the
 258 geometry and electromagnetic properties of the terrain elements.

259 To calculate the backscatter coefficient, Earth Engine uses a series of preprocessing
 260 steps implemented with the Sentinel-1 Toolbox. These steps include applying orbit files to
 261 update metadata, removing low intensity noise and invalid data on the edges of the scenes,
 262 removing thermal noise in certain acquisition modes, applying radiometric calibration values,
 263 and correcting the terrain data using either the SRTM 30 meter or ASTER DEM. The terrain
 264 correction step converts the data from ground range geometry, which does not take terrain into
 265 account, to σ^0 , resulting in a more accurate representation of the terrain.

266 In the absence of top-down data for this area, only bottom-up data were selected, and the two
 267 polarizations (VH and VV) were combined. A total of 33 images for the period from May 1st,
 268 2020 to June 1st, 2021 have been processed. For the SAR data, the ratio of VH to VV
 269 polarization (VH/VV) was calculated. Four variables were extracted from the VH, VV, and
 270 VH/VV bands over an annual time series: the median, minimum, maximum, and coefficient of
 271 variation (standard deviation divided by the mean). The dataset consisted of 102 predictor
 272 variables before being optimized through selection. (Table 3).

273

274 Table 3: A list of initial variables for classification level-1 (mangrove and land cover)

Sensor	Description	Bands name	Wavelength range	Resolution
--------	-------------	------------	------------------	------------

Spectral bands			
	Band2 : Blue	458–523 nm	10 m
	Band3 : Green	543–578 nm	10 m
	Band4 : Red	650 – 680 nm	10 m
	Band5 : Red Edge 1	698–713 nm	20 m
	Band6 : Red Edge 2	733–748 nm	20 m
	Band7 : Red Edge 3	773–793 nm	20 m
	Band8 : NIR	785–900 nm	10 m
	Band8A : Red Edge 4	855–875 nm	20 m
	Band11 : SWIR 1	1565–1655 nm	20 m
	Band12 : SWIR 2	2100–2280 nm	20 m
Spectral index		Formula	Reference
	NDVI	$(B8-B4)/(B8+B4)$	Rouse et al. (1974)
	NDWI	$(B3 - B8) / (B3 + B8)$	McFeeters (1996)
	NDMI	$(B8 - B11) / (B8 + B11)$	Gao (1996)
	DBSI	$B11 - B3)/(B11 + B3) - NDVI$	
Harmonic index <i>(calculated on the spectral indices)</i>			
	Phase	displacement between the origin and the peak of the wave in the range of 0 to 2π	Jakubauskas et al. (2002)
	Magnitude	half the value at which the function is maximized	Jakubauskas et al. (2002)
Texture information <i>(calculated on the spectral indices)</i>			Haralick et al. (1973)
	Angular Second Moment: measures the number of repeated pairs		
	Contrast: measures the local contrast of an image		
	Correlation: measures the correlation between pairs of pixels		
	Variance: measures how spread out the distribution of gray-levels is		
	Inverse Difference Moment: measures the homogeneity		
	Sum Average		
	Sum Variance		
	Sum Entropy		

Entropy: Measures the randomness of a gray-level distribution
 Difference variance
 Difference entropy
 Information Measure of Corr. 1
 Information Measure of Corr. 2
 Dissimilarity
 Inertia
 Cluster Shade
 Cluster prominence

Sensor	Description	Bands name	Centre frequency	Resolution
Sentinel-1	SAR	VH- ascending	5.405 GHz	X: 10 m Y:10 m
		VV- ascending	5.405 GHz	X: 10 m Y:10 m
		VH/VV		
	SAR statistics on the time series (calculated on <i>VHasc</i> , <i>VVasc</i> , <i>VHasc/VVasc</i>)	Minimum		
		Maximum		
		Median		
		coefficient of variation		

275

276 **3. Methods**

277 The complete methodological flowchart is shown in Figure 2. This method is divided into two
 278 levels:

279 Level 1: Mapping the mangroves and land use required for linear spectral unmixing

280 Level 2: Mapping vegetation formations by object-based spectral-temporal feature
 281 classification

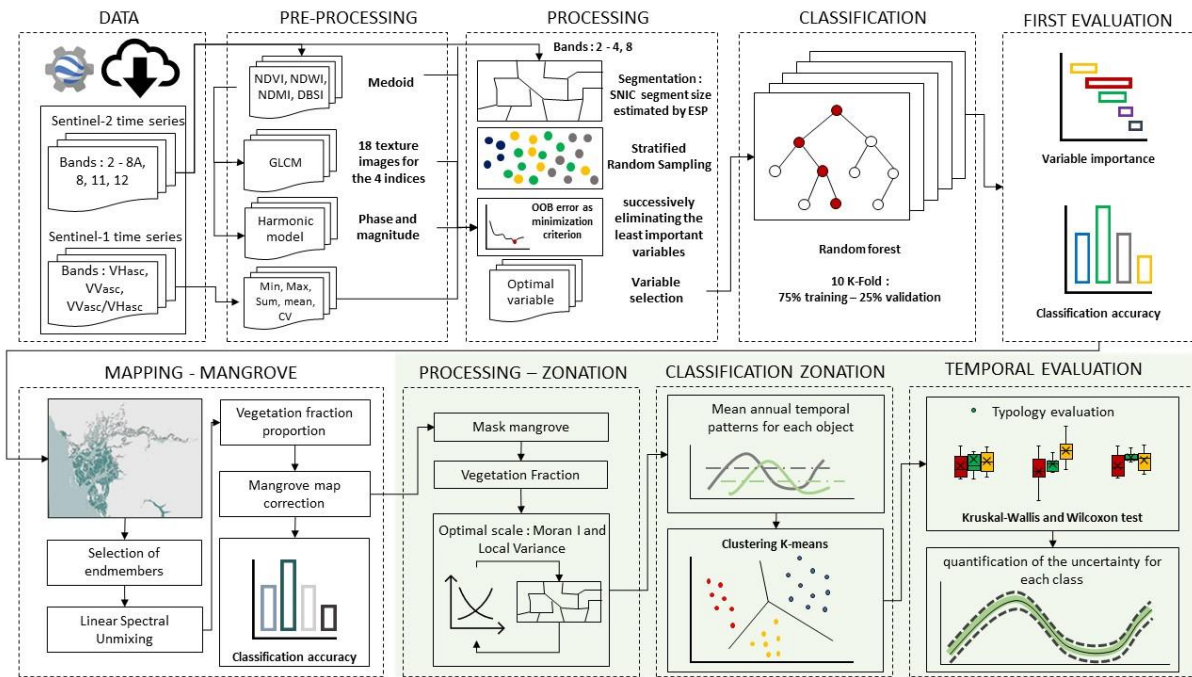


Figure 2: Flowchart of the proposed approach.

At white background: treatments allowing to obtain a cartography of the mangrove.

At light green background, treatments allowed us to obtain a cartography of mangrove plant formations.

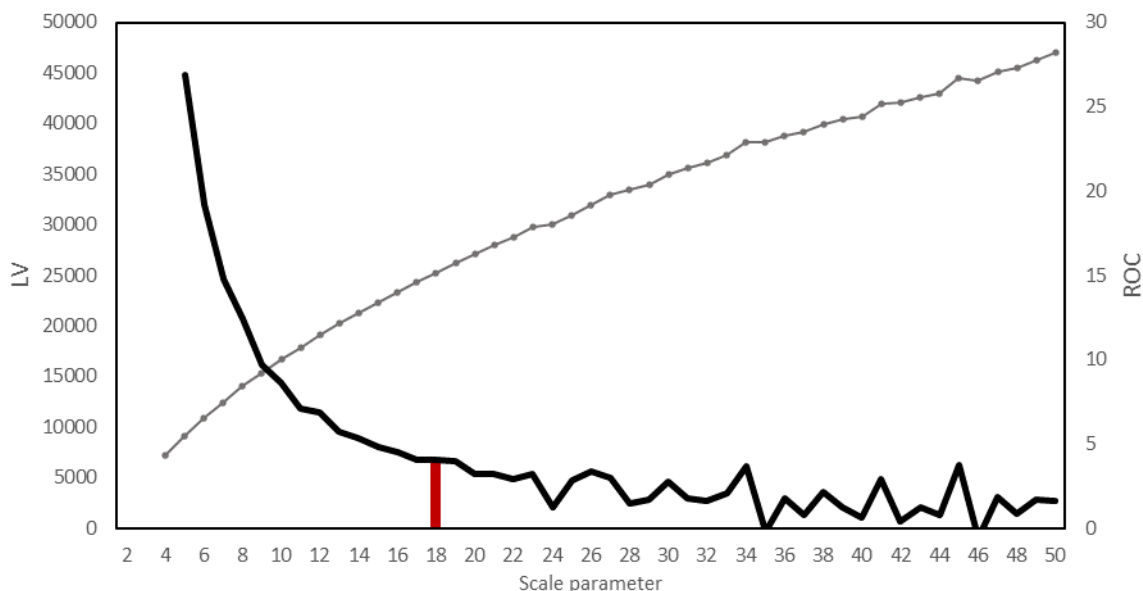
3.1. Mangrove and land cover mapping (Level-1)

First, the mangrove is mapped using a combination of OBIA and machine learning approaches, specifically Random Forest. Although the pixel approach has been extensively used for mangrove classification (Bunting et al., 2018; Mondal et al., 2019; Jia et al., 2021; Lu and Wang, 2021; Lui et al., 2021; Xiao et al., 2021), we chose an object approach (Myint et al., 2008; Wang et al., 2018; Wang et al., 2021) to reduce spectral confusion by smoothing the dataset features within objects and reducing the statistical noise of the images (Blaschke et al., 2008; Blaschke, 2010; Dronova, 2015; Hossain and Chen, 2019). This reduces the complexity of the images and the size and dimensionality of the dataset. In addition, the optimal features for classification were evaluated. With textural characteristics, objects appear as a privileged entity to evaluate the importance of texture indices (GLCM) in classifying inter-tidal areas.

3.1.1. Segmentation

Segmentation is the first classification process. The superpixel clustering approach based on simple non-iterative clustering (SNIC) using the GEE was chosen. Bands with the highest optical spatial resolution only (B2, B3, B4, and B8) were implemented. The SNIC algorithm (Achanta and Süsstrunk, 2017) uses a regular grid of 'seeds' as the initial centroid of the superpixel. The parameterization of the algorithm requires the specification of superpixel seed spacing (in pixels). The larger the spacing, the larger the object size. Therefore, it is critical to scale parameters. Several methods have been developed to determine the optimal threshold for the scale parameters (Ma et al., 2017). The scale parameter estimation (ESP) initially proposed by Drăguț et al. (2010) and modified for multispectral imagery (Drăguț et al. 2014) was chosen because of its low computational cost, and therefore, could be applied to large areas. For each 2–50-pixel spacing step, the local variance was calculated for each band and then averaged

311 (Drăguț et al. 2014) for fixed values of connectivity at 8 and compactness at 1. The rate of
 312 change (ROC) was then calculated for each scale change. The first break in the curve after
 313 continuous decay is the threshold at which significant objects emerge. In other words, the scale
 314 value showing for the first time a negative change (Figure 3) in the ROC curve was selected as
 315 the optimal seed spacing value.



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317

Figure 3: Estimate scale parameter.

318 The graphs show the changes in local variance (LV) (black) and rate of change (ROC) (gray dots) with
 319 increasing scale parameters. Vertical lines in red indicate the optimal scaling parameters selected for Saloum

320

321 3.1.2. Training and validation samples

322 The training and validation of machine learning classifications require reference sample data
 323 for land cover. Four classes were referenced: Water, Mangrove, Salt flats, Other land covers
 324 (all continental surfaces, including bare soil, other vegetation, urban, and cropland). Reference
 325 data collection followed a labeling procedure using ESRI (2017) and Google Earth (2018,
 326 2021) high-resolution imagery, with a Sentinel-2 color composition check from 2021 to ensure
 327 the class stability spotted on slightly older THRS imagery.

328 Stratified random sampling was applied to avoid bias during the validation (Olofsson
 329 et al., 2014). Therefore, a random draw was performed in the nine classes of the ESA
 330 WorldCover 10 m 2020 v100 map (Zanaga et al., 2021) with 400 points per class. This map
 331 had an overall accuracy of 74.4%; therefore, we removed or corrected erroneous data. After
 332 filtering, 2592 reference samples were collected, of which 75% and 25% of the samples were
 333 retained for training and mapping validation, respectively. For model training, 223, 312, 322,
 334 and 1,660 samples were retained for water, mangrove, salt flats, other land covers, respectively.
 335 The objective was to obtain a statistical representation of the different land cover types within
 336 the dry land class. For model validation, 74, 77, 80, and 414 samples from water, mangrove,
 337 salt flats, other land covers, respectively, were selected.

338 *3.1.3. Classification processing and accuracy assessment*

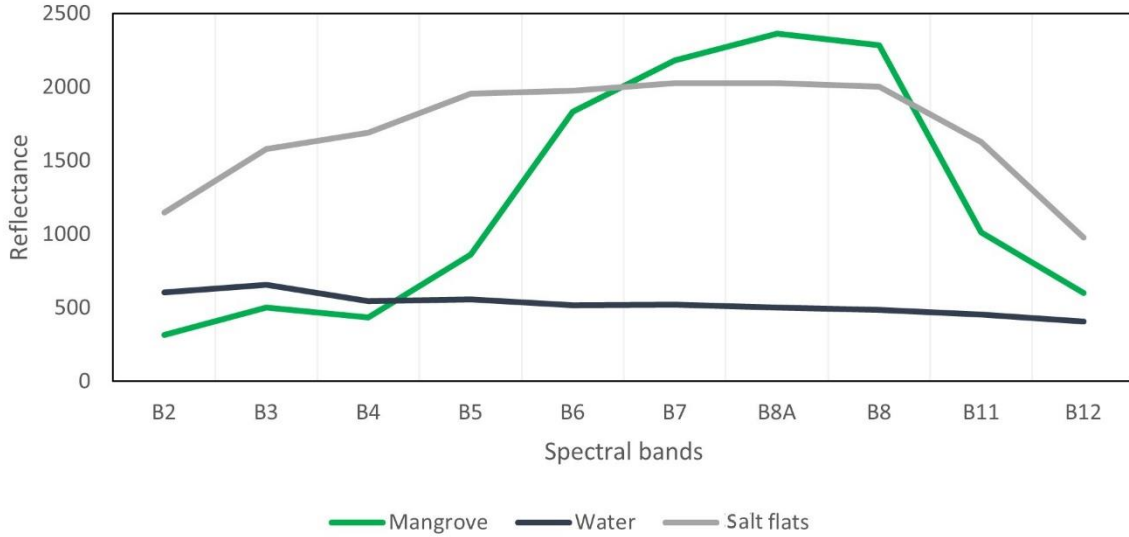
339 The classification into water, mangrove, salt flats, other land covers was performed using the
340 random forest algorithm (Breiman, 2001) on the GEE platform. Although the random forest
341 model has the ability to handle many variables (Belgiu and Dragut, 2016), we chose to reduce
342 the dimension of the dataset by retaining only the so-called optimal variables. To develop
343 simple and parsimonious classification models, the use of a variable selection algorithm allows
344 the maintenance of a small number of variables. This will allow for fewer data collection
345 procedures in the future and a more efficient evaluation of the variable importance. Speiser et
346 al. (2019) mentioned that reducing the number of variables in random forest models can also
347 improve the efficiency of classification. To address these objectives, a backward elimination
348 approach was used, based on model performance as a function of the rate of change in
349 classification accuracy when adding or removing variables (Díaz-Uriarte and De Andres,
350 2006). The VarSelRF package in R statistical software was used to select variables. The ‘Out
351 of Bag’ (OOB) error was used as a minimization criterion and the least important variables
352 were eliminated. In each iteration, 10% of the variables were eliminated. This procedure was
353 repeated 20 times, as recommended by Li et al. (2016) and Wang et al. (2018), to select a subset
354 of the most important features. To assess the stability of the classifications, a 10-fold repeated
355 cross validation was undertaken. The accuracy scores for mangrove, inter-tidal, and upland
356 classifications were obtained using a confusion matrix (Stehman 1997). Overall accuracy (OA),
357 producer accuracy (PA), user accuracy (UA), and kappa coefficients were generated. Finally,
358 an overall F1 score was used to obtain the accuracies for each land cover class.

359

360 *3.2. Mangrove zonation mapping (Level-2)*

361 We also used the OIBA approach to map mangrove zonation by discriminating its plant
362 formations. Segmentation is a crucial step and is performed using a linear spectral unmixing
363 image of the vegetation fraction. The first mapping allowed for the selection of the
364 endmembers. Based on the model of Taureau et al. (2019), we decomposed the pixel intensity
365 into three endmembers, each representing a component of the mangrove ecosystem.: water,
366 mangrove and salt flats. The 10th decile of the mangrove NDVI was retained. Mudflats with
367 the lowest coefficient of variation of NDWI were chosen for their spectral stability throughout
368 the year. Non-turbid water spectral was obtained by unsupervised classification of the water
369 mask into 30 classes and selection of the spectral signature with the lowest reflectance values
370 in the Sentinel-2 optical bands. The spectral signatures of the endmembers are shown in Figure
371 4.

372



373

374 **Figure 4:** Spectral reflectance curves for water, mangrove, and salt flats selected for linear spectral unmixing.

375

376 Four images were generated to represent the contribution of each endmember to each
 377 pixel. Therefore, the pixels misclassified during the first step could be partially corrected by
 378 considering the most important contribution of the endmember to definitively assign the classes
 379 of mangrove, salt flats, and water. We preferred the OBIA approach in the first instance because
 380 the optimal object size avoids confusion between mangroves and dense dryland vegetation that
 381 was obtained using the pixel approach. Nevertheless, the optimal object size was calculated
 382 globally, not locally. Therefore, objects that are too large in areas of mangrove vegetation that
 383 combine water and salt flats may remain. Hence, Linear Spectral UnmixingLSU allows the
 384 pixels to be reassigned to the right classes within the objects.

385 3.2.1. Segmentation and spatial structure of the mangrove

386 Intra-mangrove segmentation is a key step in determining homogeneous features that reflect
 387 mangrove distribution along environmental gradients. The SNIC algorithm under GEE was
 388 used again by varying the superpixel seed spacing in steps of 1 and up to a spacing of 20. We
 389 considered that the ‘optimal’ intra-mangrove objects could not be larger than 20, because the
 390 optimal scale parameter for land cover classification was 18. The choice of the segmentation
 391 scale parameter is crucial because it will have important consequences on the clustering and
 392 thus the typology of vegetation formations. To better detect transitions within the mangrove,
 393 the selection of the optimal scale parameter must meet the criteria of intra-segment
 394 homogeneity and inter-segment heterogeneity (Espindola et al., 2006; Johnson and Xie, 2011;
 395 Johnson et al., 2015). For this purpose, the most common method is to calculate the weighted
 396 variance (wVar) as an indicator of intra-segment spectral homogeneity (Eq. 1) and the Moran
 397 Index (MI) to measure the inter-segment spectral heterogeneity (Eq. 2).

$$398 \quad wVar = \frac{\sum_{i=1}^n a_i \times v_i}{\sum_{i=1}^n a_i} \quad (1)$$

399 where n is the total number of objects

400 v_i and a_i are the variance and area of the object i , respectively. Large objects have a greater
 401 impact on the overall variance than small ones.

402

403

$$MI = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^n (y_i - \bar{y})^2 (\sum_{i \neq j} \sum w_{ij})} \quad (2)$$

405

406 where n is the total number of objects

407 y_i and \bar{y} are the average spectral values of the object i and the whole image

408 w_{ij} is a measure of the spatial proximity between object i and j .

409

410 For the calculation, the objects were in a vector format. We considered the adjacency
 411 of the segments as spatial proximity; if a single vertex of an entity is adjacent to another entity,
 412 these two segments are neighbors. Therefore, we constructed a matrix of spatial weights.
 413 Several studies (Johnson and Xie, 2011; Wang et al., 2021) have set the values of w_{ij} to zero
 414 (non-neighbor) or one (neighbor). Binary matrices can induce statistical bias, generating
 415 different weights for individuals depending on their neighbor numbers. To overcome this
 416 problem, in-line standardization of the matrix was performed. Thus, the sum of the weights in
 417 each row is equal to one. This operation was performed with the package ‘spdep’ in R (Bivand
 et al., 2015).

418

419 The values of wVar and MI were normalized for comparison according to the following

420 normalization formula (eq. 3):

$$X_{norm} = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (3)$$

421

422 Where X_{norm} is the normalization of the values of wVar or MI.

423 X_{min} is the minimum value of wVar or MI.

424 X_{max} is the maximum value of wVar or MI.

425

426 Finally, the F-measure was calculated (eq. 4) to capture the best compromise between
 427 intra-homogenous and inter-heterogenous segmentation (; Johnson et al., 2015; Wang et al.,
 428 2019).

$$F = \frac{1}{\alpha \frac{1}{wVar} + (1-\alpha) \frac{1}{MI}} \quad (4)$$

430

431 where α (between 0 and 1) is the relative weight of the normalized values of wVar and MI.
 432 Thus, intra-segmental homogeneity or inter-segmental heterogeneity can be assigned higher
 433 importance. In this study, the weights of the two indices are considered the same. Therefore,
 the weight was set as $\alpha = 0.5$. A large F-value indicates high-quality segmentation.

434 3.2.2. Clustering of mangrove zonation

435

436 To capture this cycle, the time series of the plant fraction was modelled using harmonic
 437 regression in GEE (Clinton, 2016). This method has been shown to be relatively effective in
 describing mangrove zonation patterns in semi-arid areas with Sentinel-2 images (Valderrama-

438 Landeros et al., 2021). Therefore, regression models with harmonics were used. We fitted and
439 calculated the harmonic coefficients and extracted the amplitude (seasonal variability), annual
440 trend (annual average), and RMSE (non-seasonal variability) to characterize the phenological
441 patterns of the different objects (Pasquarella et al., 2018). Model fit was better for harmonic
442 regressions based on fractional components from linear unmixing than for spectral indices,
443 justifying the use of the vegetation fraction instead of NDVI. The objective here is to
444 discriminate these zonations on an annual basis rather than revealing the variation itself. The
445 annual average is indeed a feature that mostly influences classification.

446 The small sample size from the field made the training and validation process of a
447 supervised classification difficult; therefore, unsupervised classification with the K-means
448 algorithm was preferred. The objective was to obtain a typology aimed at maximizing the
449 contrasts between classes while reflecting the zonation and physiognomy of the vegetation.
450 Field data were used to interpret the clusters. To ensure the overall significance of the classes,
451 the Kruskal-Wallis test was performed. In addition, pairwise multiple comparisons between
452 groups were used to evaluate the significance between classes using the Wilcoxon test. These
453 tests were performed with field-derived variables, such as cover rate, stand height, and species
454 dominance. These tests were performed with all variables of the harmonic model describing
455 seasonality and with different numbers of classes from two to six. To evaluate the significance
456 of the differences between classes, the threshold p-value of 0.01 was retained.

457 3.2.3. Stability assessment of the typology

458 The detection of mangrove zonation typology must be reproducible over time to ensure its
459 monitoring and reliably interpret its changes. Indeed, a typology in which the classes do not
460 have enough contrast at certain times of the year could lead to errors in detecting changes.

461 To evaluate typology and temporal stability, we used a three-step process. First, the
462 methodological chaining presented so far was repeated on the data from 01/11/2019 and
463 01/11/2020. An intersection between the two classifications allowed us to isolate the objects
464 assigned to the same class on both dates, which did not undergo any major changes. Finally,
465 these were used as a basis for training (70% of the objects) and validation (30% of the objects)
466 of the Bayesian model. For this stage, the probabilities of membership were calculated using
467 Bayes' theorem.

$$468 \quad p(h | e) = \frac{p(e | h) \times p(h)}{\sum_i p(e | h_i) \times p(h_i)} \quad (5)$$

469 where $p(h | e)$ is the probability that hypothesis (h) is true, given the proof (a posteriori
470 probability noted e).

471 $p(e | h)$ is the probability of finding that the evidence provided by hypothesis (h) is true (from
472 the training data).

473 $p(h)$ is the probability that the hypothesis is true, regardless of the evidence (a priori
474 probability).

475 A series of images expressing the *a posteriori* probability of belonging to a set of plant
476 formation classes were generated. The objective of this study was to evaluate the degree of
477 belonging of an object to a class according to the vegetation fraction on both dates. Hard

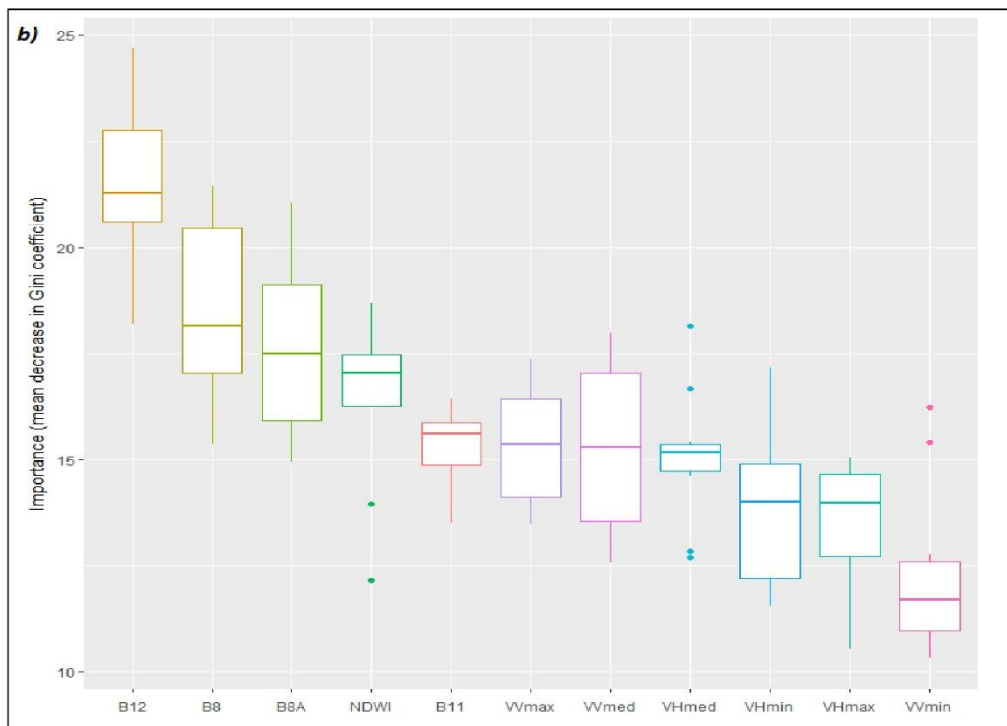
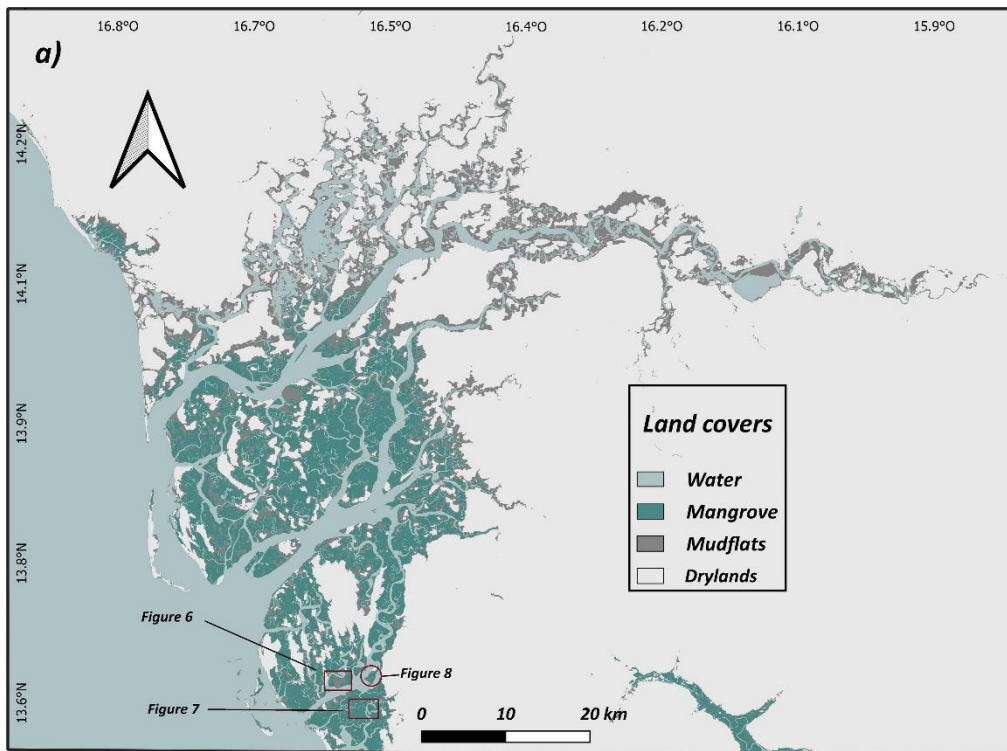
478 classification was used to obtain a thematic map. For each object, the class with the highest
479 probability was assigned.

480 Finally, the probable confusion over time was evaluated for each class by noting the
481 frequency of false predictions of the Bayesian model for each value of the vegetation fraction.
482 The objective of this experiment was to quantify the amplitude of the fluctuations in plant
483 fractions that can be interpreted as a change in the spatial structure of mangrove zonation.

484 **4. Results**

485 ***4.1. Mangrove mapping***

486 At the end of the RF classification of the objects, the Saloum mangrove map (Figure 5a)
487 presented relatively high accuracy scores (Table 4) using a reduced dataset of 11 discriminating
488 variables. After ten cross-validations, the optical bands in the NIR and SWIR wavelengths
489 proved to be the most effective for mapping the mangrove in this environment, followed by the
490 SAR data (Figure 5b). From then on, the SAR data constituted more than 50% of the selected
491 variables. Texture variables and time-series harmonic model coefficients were negligible for
492 the desired land cover discrimination. Finally, 11 variables were selected: VHmin, VHmed,
493 VHmax, VVmin, VVmed, VVmax for SAR data and B8, B8A, B11, B12, NDWI for optical
494 data. The consistent appearance of SAR data in the group of optimal variables suggests that it
495 is a valuable source of information for understanding and predicting the distribution and
496 behavior of the studied system. In contrast, when optical bands like B8 or B8A were present in
497 the group of variables, they tended to contribute more to the discrimination of the surface states
498 of the selected typology.



499

500 **Figure 5a:** Random Forest classifications using Sentinel-1 and Sentinel-2 data (left) from an optimal dataset.

501 Locations refer to the following figures that focus on mangrove zonation

502 **Figure 5b:** Optimal dataset and variables importance.

503 The importance of the variables was measured by the average decrease in the Gini index of the nodes and leaves
 504 in the resulting random forest. This expresses the degree of precision that the model loses by excluding each
 505 variable.

506

507 Table 4 shows that the average overall accuracy is 97.12% and the Kappa index is
 508 94.6%. Within the Sine-Saloum region, mangroves obtain the highest average relative accuracy
 509 scores (F1-score = 98.55%) among the land cover types. Drylands has similar scores, and salt
 510 flats had the lowest average accuracy with an F1-score of 88.31. On the other hand, the
 511 classifications are relatively stable. Indeed, the standard deviation for the global accuracies and
 512 Kappa index are 0.008 and 0.015, respectively. The surfaces and their fluctuations were
 513 quantified according to the classifications. The water and mangrove areas varied respectively
 514 by an average of 0.37% and 0.47%, that is, 721 ha and 317 ha. Variations of 0.1%, that is 756
 515 ha, were observed on average for the drylands. Finally, the salt flats showed more important
 516 fluctuations in the estimation of their surfaces, of the order of 2% or 1029 ha.

517

518 Table 4 shows that the contribution of post-classification linear spectral unmixing
 519 brings a slight gain in overall precision (+ 0.99%) and (+ 1.88%) on the Kappa index. We also
 520 observed a significant gain in relative precision class by class. Nevertheless, the LSU
 521 contribution is sometimes better at the pixel level than at the object level, notably for water (F1
 522 score = + 1.95 against 1.39 for RF-OBIA + LSU-OBIA) and mangroves (F1 score = + 0.36%
 523 against -1.33 for RF-OBIA + LSU-OBIA). Given the scores and the purpose of this paper, the
 524 mangrove areas from the RF-OBIA + LSU method were retained for mapping the vegetation
 525 formations.

526

527 Table 4: Scores assessing the accuracy of the classifications and their impact on the quantification of Land
 528 Cover types

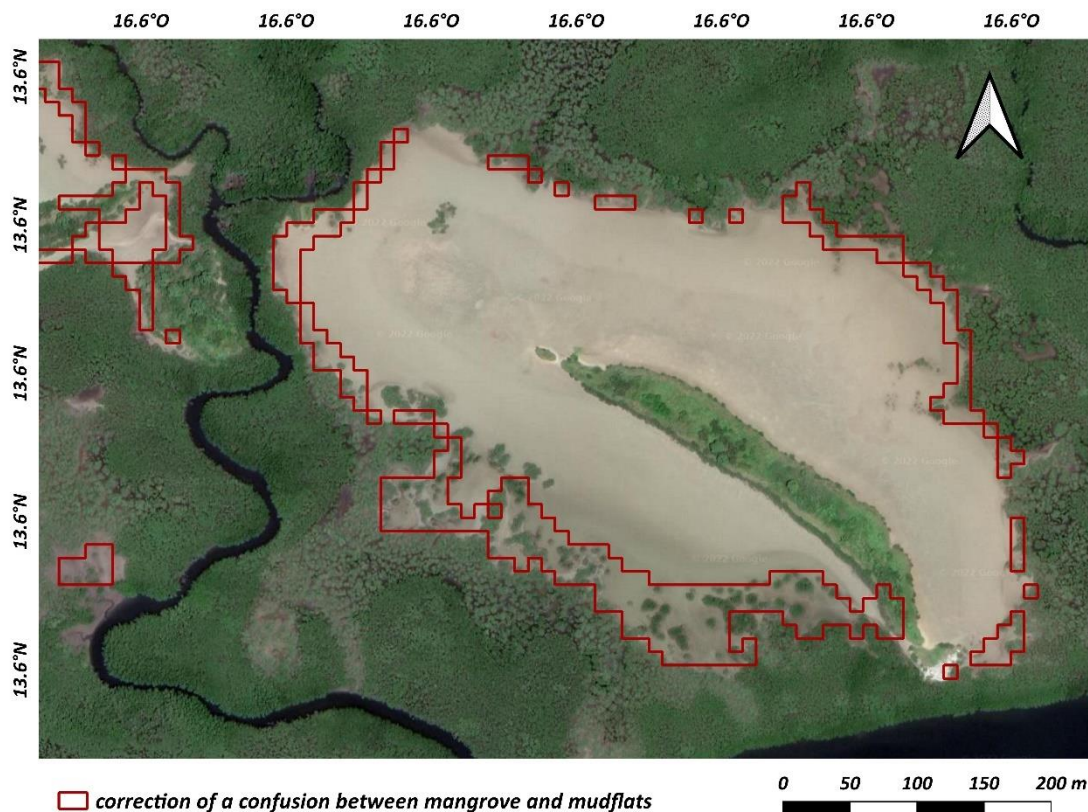
<i>Accuracy</i>	<i>OA %</i>		<i>Kappa %</i>		<i>F1 - Score %</i>			
	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Water</i>	<i>Mangrove</i>	<i>Salt flats</i>	<i>Drylands</i>
<i>(RF-OBIA)</i>	97.12	0.8	94.6	1.5	96.30	98.55	88.31	98.53
<i>(RF-OBIA + LSU-OBIA)</i>	98.11	0.8	96.48	1.5	97.69	97.22	92.16	99.46
<i>(RF-OBIA + LSU)</i>	97.55	0.9	95.42	1.7	98.25	98.91	90.10	99.35
<i>Area</i>	<i>Area (ha)</i>				<i>Std Area (ha)</i>			
	<i>Water</i>	<i>Mangrove</i>	<i>Salt flats</i>	<i>Drylands</i>	<i>Water</i>	<i>Mangrove</i>	<i>Salt flats</i>	<i>Drylands</i>
<i>(RF-OBIA)</i>	193 214	67 762	50 380	750 382	721	317	1 029	756
<i>(RF-OBIA + LSU-OBIA)</i>	192 843	65 341	53 188	749 373	-	-	-	-
<i>(RF-OBIA + LSU)</i>	193 578	63 124	54 762	750 272	-	-	-	-

529

530 The linear spectral unmixing measuring, within a pixel, the fraction of each land cover
 531 showed that the initial (object-based random forest) classification overestimated the mangrove
 532 areas by an average of 4638 ha or 6.84%. The consequent decrease in mangrove surfaces with
 533 the RF-OBIA + LSU approach coincided with the increase in salt flats surfaces. Therefore, the
 534 main confusion concerns the mangroves and salt flats. Of the mangrove surfaces, 6.43% were

535 classified as salt flats using the RF-OBIA + LSU approach, and 0.42% as water. Therefore,
536 93.5% of the classification differences between the two approaches concerned mangroves and
537 saltflats (Figure 6).

538
539
540
541



542
543 **Figure 6:** Example of correction of the RF-OBIA +LSU approach. Red contours represent areas classified as
544 mangrove before correction and as salt flats after correction. Most of the confusion concerns the mangrove-salt
545 flats interface.

546

547 4.2. Mangrove zonation mapping

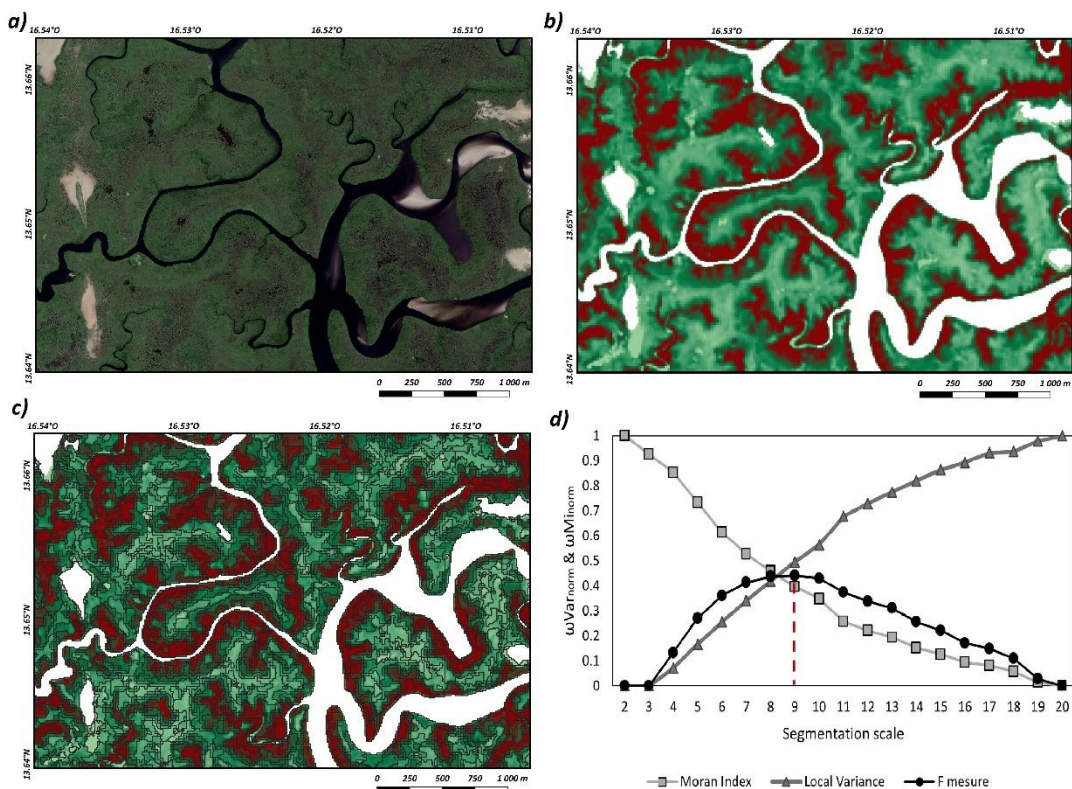
548 4.2.1. Optimal scale

549 Figure 7 shows the optimal scale obtained by maximizing inter-segment heterogeneity and
550 intra-segment homogeneity. A spacing of nine pixels allows the SNIC approach to achieve an
551 optimal global trade-off. The spacing from 2 to 11 pixels generated objects with a very different
552 internal variance from one spacing to the other, increasing faster before the slope of the curve
553 became smoother. The Moran index decreased consistently over the same interval, meaning
554 that the objects diverge increasingly from their neighborhood. The F-metric allows the best
555 global compromise to be synthesized. Therefore, the tested spacings from 2 to 8 induced a
556 satisfactory internal homogeneity of the objects, but an extremely low global inter-object
557 heterogeneity. A spacing of 2–8 induced over-segmentation; thus, the tested spacings from 10

558 to 20 induced extremely low intra-object homogeneity, but acceptable global inter-object
 559 heterogeneity. Therefore, we concluded that a spacing of 10–20 induces under-segmentation.

560 Figure 7 shows the consequences of the chosen scale on vegetation fraction index segmentation
 561 (Figures 7b and 7c). A THRS Google Earth image (Figure 7a) allows for apprehending the
 562 grain of the vegetation, its retranscription by the vegetation fraction index (Figure 7b), and the
 563 consideration of its spatial structure by segmentation (Figure 7c). Visually, the strong values
 564 of the index (in red) synonymous with a high and dense mangrove, often at the edge of banks,
 565 seem well-captured as a single object by the OBIA approach. On the other hand, some places
 566 where the index is lower and where the vegetation cover appears less dense on the THRS image
 567 appear oversegmented.

568



569

570

Figure 7: Optimal segmentation scale for detecting homogeneous plant formations.

571

a) High resolution Google Earth image of South Saloum

572

b) The vegetation fraction index from linear unmixing (Red values represent the largest vegetation fraction and can be equated with dense, high shoreline mangroves. The green gradient can be assimilated into the decrease in the density and height of the mangrove along the foreshore)

573

574

c) Optimal object segmentation

575

576

d) Results of optimal scale parameter detection. The 9 pixels spacing for SNIC segmentation is the best

577

compromise between intra-homogenous and inter-heterogeneous segmentation.

578

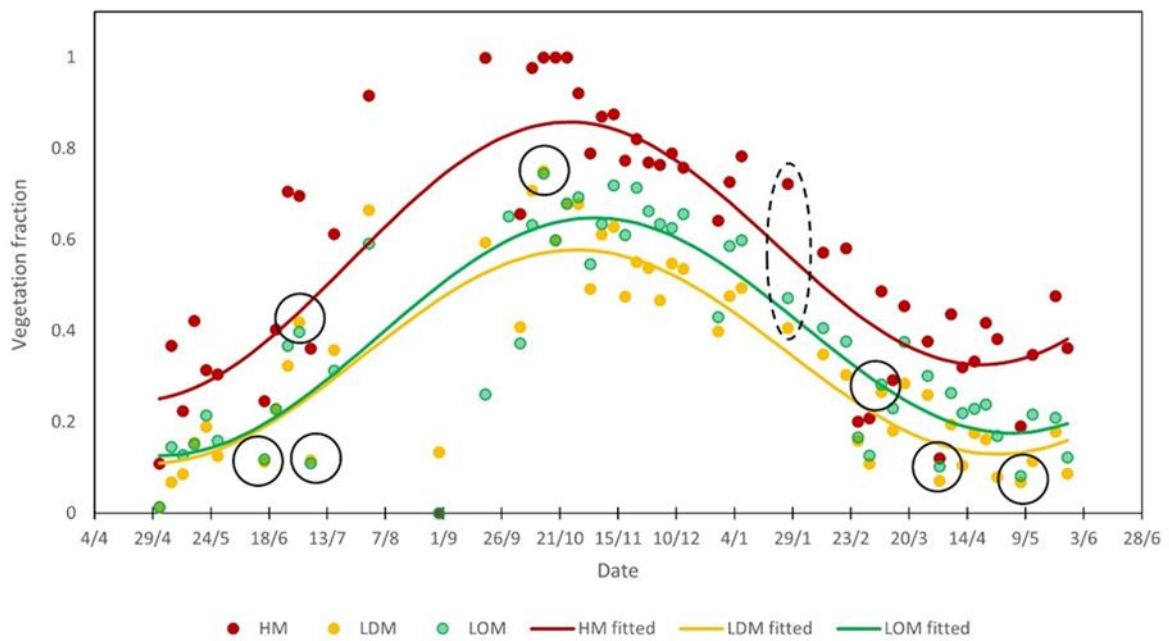
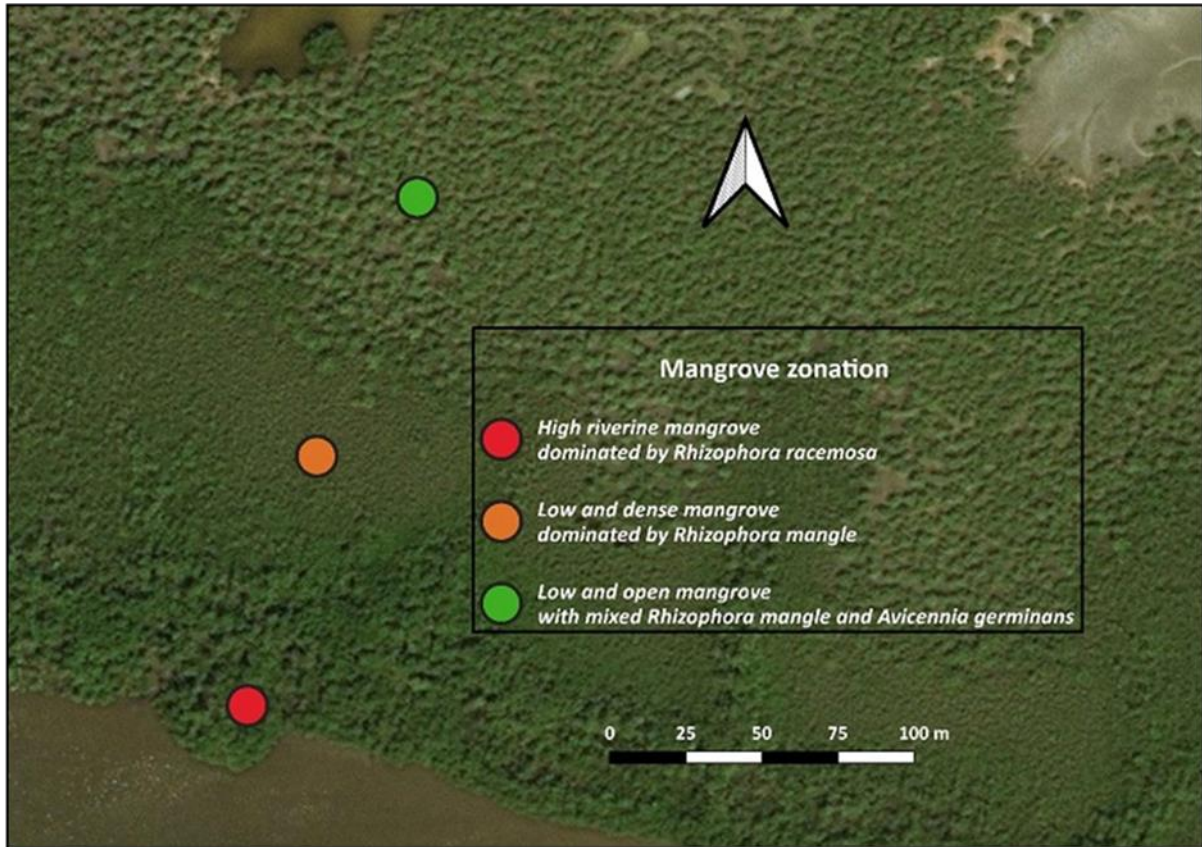
579

580

4.2.2. Spectral Seasonality-Based Mangrove Zonation Classification Using Spatial Objects

581 The vegetation indices of these mangroves followed a seasonal pattern that could be captured
582 by the vegetation fraction of a pixel. High values of the vegetation fraction index were
583 observed during the rainy season, mainly from August onwards. A decrease in these values
584 was observed at the end of the rainy season in November.

585 The discrimination of mangrove plant formations by time-series analysis meets the objective
586 of developing a reliable and robust typology over time. Figure 8 shows that during the course
587 of the year, the values of the indices do not always capture contrasts in the spatial structure of
588 the vegetation. Indeed, at the end of the dry season, there were sometimes no differences in
589 plant fraction index values between the two plant formations. The values obtained for
590 18/06/2020 and 02/04/2021 (fig. 8) were similar between the high bank mangrove (HM) and
591 the low and dense mangrove (LDM), and between the latter and the low and open mangrove
592 (LOM). Therefore, single-date images and classifications based on the values alone may be
593 inoperable.



594

595

Figure 8: Annual phenological patterns of mangrove zonation.

596 On the x-axis, the time axis ranges from 2020-05-01 to 2021-06-01. On the y-axis, the vegetation fraction values
 597 from the linear spectral unmixing are shown.

598

The points represent the values within the time series for each class.

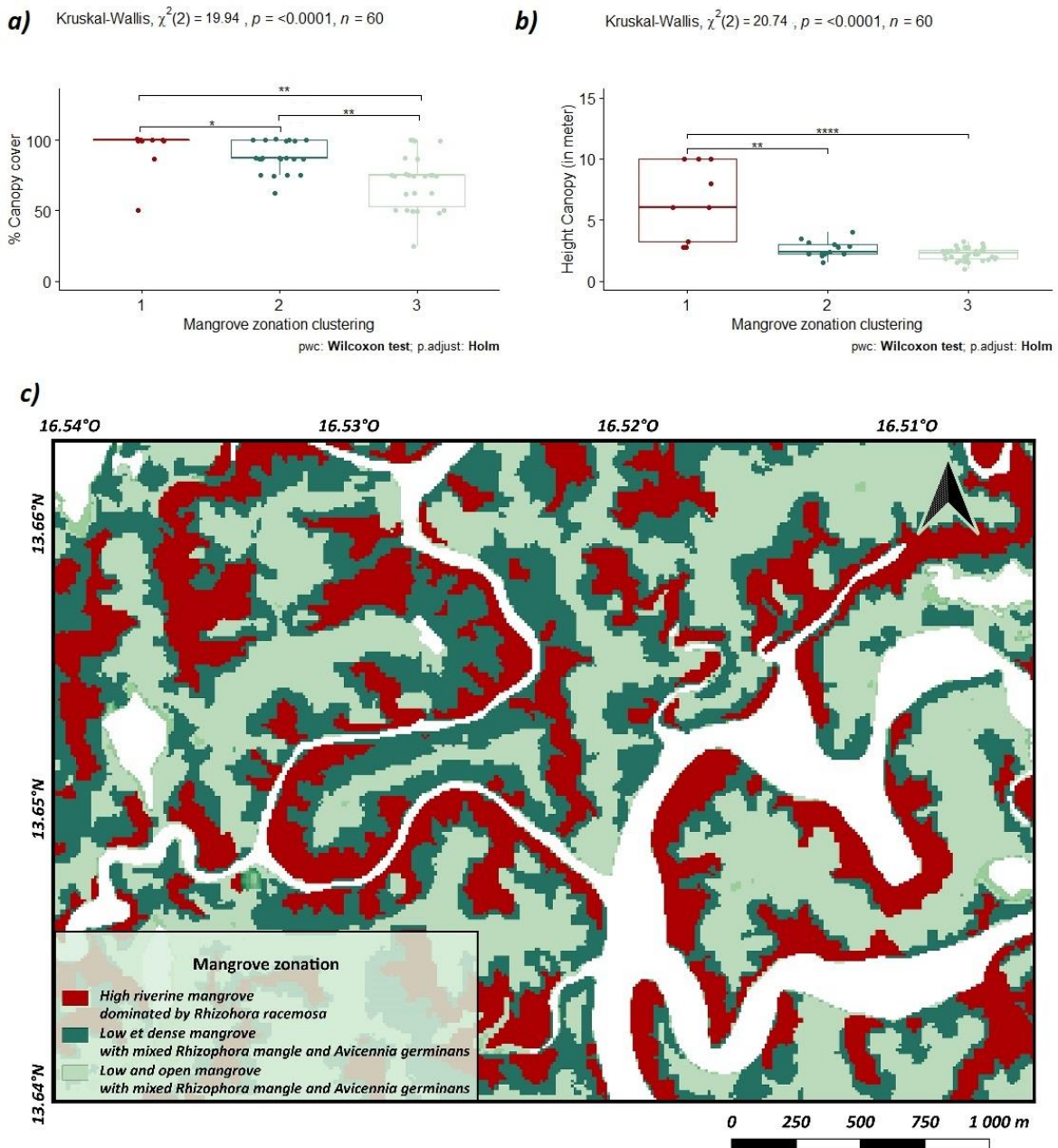
599

The solid lines represent the harmonic regression model for each class.

600 Solid line ellipses show the likely confusion between thematically different classes. The dashed ellipse
601 represents the date when spectral sparsity is maximized.

602 HM : High mangrove – LDM : Low and dense mangrove - LOM : Low and open mangrove

603 Figure 9 shows the mangrove zonation clustering for 2021 and a visual comparison with
604 Google Earth © images. The number of classes was determined from field data. The Kruskal-
605 Wallis test was used to ensure the overall significance of the classes. The Wilcoxon test was
606 used to determine whether the typology presented significant differences between classes with
607 the parameters found in the field. The results of the different tests show that clustering based
608 only on the annual average of the values modelled by harmonic regression and with three
609 classes made the most thematic sense. These results indicate that the density of vegetation cover
610 contributes significantly (p-value = 0.00057) to the discrimination of facies using the proposed
611 approach. The three-class typology based on canopy height, canopy openness, and color
612 appeared to fit well with the spatial resolution of the Sentinel-2 images (Figure 9). The
613 differences in height between the second and third classes were not statistically significant (p-
614 value = 0.102). Therefore, these two classes were denoted as low mangroves. Nevertheless, the
615 proposed approach does not allow for the differentiation of mangroves at a specific level. It
616 also does not allow for a significant determination of the abundance of species within the
617 classes (Supplemental material). Therefore, a typology based on height, density of vegetation
618 cover, and the presence/absence of plant species was adopted (Figure 9, Supplemental
619 material). Finally, the morphology of the classes and their locations (Figure 9) seem to agree
620 with the high-resolution data and with theoretical and empirical knowledge of the field (Sow
621 et al., 1991; Ndour et al., 2012; Andrieu et al., 2020).



622

623

Figure 9: Mangrove zonation clustering

624 (1: High riverine mangrove dominated by *Rhizophora racemosa*; 2: Low et dense mangrove with mixed

625 *Rhizophora mangle* and *Avicennia germinans*; 3: Low and open mangrove with mixed *Rhizophora mangle* and

626 *Avicennia germinans*)

627 a) Significance of the differences between classes for the overlap rate.

628 (The results of the Kruskal-Wallis test are available at the top of the figures)

629 b) Significance of the differences between classes for the average height of the individuals

630 (Only the results of the significance tests appear in this figure).

631 c) Map of the mangrove zonation for the year 2021

632 The high mangrove facies have patches with rather long morphologies and are located at the

633 edge of the channel. Patches of this class located in the middle of a mangrove area may indicate

634 the presence of a small channel that is completely covered by a closed canopy. The low and

635 open mangrove facies showed a less elongated morphology and were consistently found at the
 636 interface with the salt flats. Finally, the low and dense mangrove facies were generally located
 637 between the other two classes, representing the transition between high-density and open
 638 mangroves. The ground-truth data also confirmed that not all riverine mangrove facies were
 639 necessarily high. In most concave meanders of channel banks, mangrove forests were medium
 640 and dominated by the *Rhizophora mangle*. Conversely, in most convex meanders of banks,
 641 mangrove forests were abundant and dominated by *Rhizophora racemosa*.

642 **4.3. Temporal accuracy**

643 Figure 10 shows the confounding probabilities for each class as a function of the plant fraction
 644 values. These reflect the average values obtained by harmonic regression between 2019 and
 645 2021. The overall expected accuracy for classifying the mangrove plant formations in the
 646 Saloum Delta was 85.5% (Table 5). Confusion probabilities were the highest in classes that
 647 often have spatial contiguity in zonation. Consequently, the class ‘Low and dense mangrove
 648 with mixed *Rhizophora mangle* and *Avicennia germinans*’ had the highest prediction error rate.
 649 This class is likely to be confused with the ‘High riverine mangrove dominated by *Rhizophora*
 650 *racemosa*’ class with a probability of 5.8%, and with the ‘Low and open mangrove with mixed
 651 *Rhizophora mangle* and *Avicennia germinans*’ class with a probabbility of 8.3%. Table 5
 652 presents the confusion matrix from the Bayesian classification. Logically, the prediction errors
 653 between the two classes located at the lowest and highest positions of the foreshore were
 654 negligible.

655

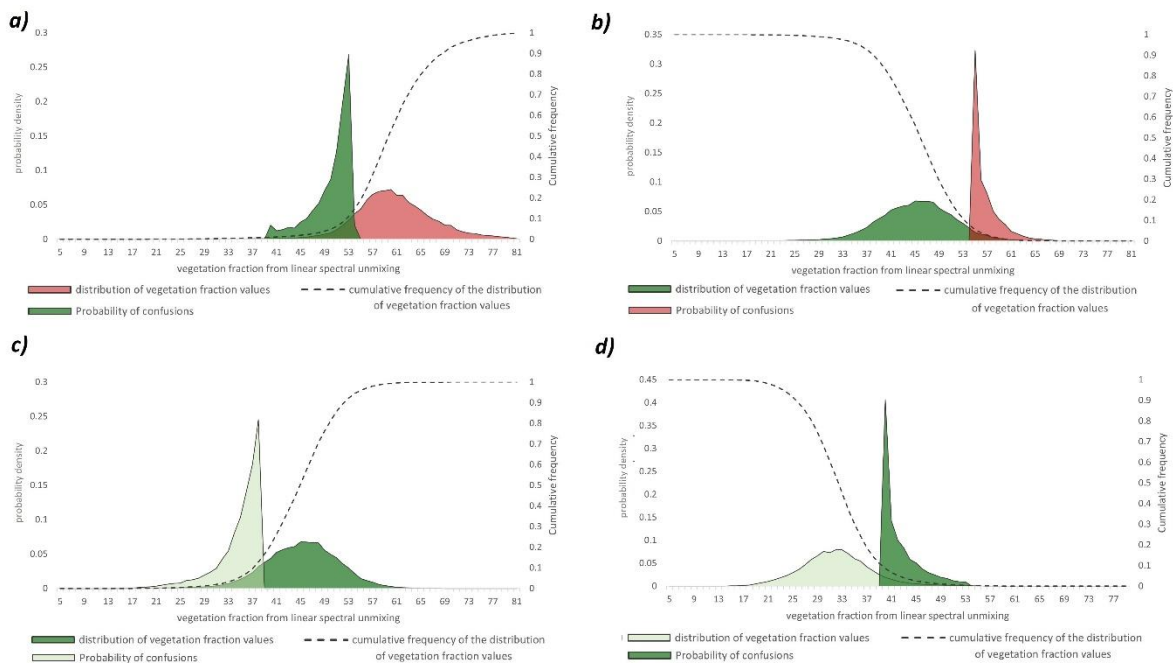
656 Table 5: The error matrix for the period (2019-2021) using a Naïve Bayes classification approach on stable
 657 objects (results are expressed as a proportion).

Class	Reference data		
	High riverine mangrove dominated by <i>Rhizophora racemosa</i>	Low and dense mangrove with mixed <i>Rhizophora mangle</i> and <i>Avicennia germinans</i>	Low and open mangrove with mixed <i>Rhizophora mangle</i> and <i>Avicennia germinans</i>
High riverine mangrove dominated by <i>Rhizophora racemose</i>	26.3 %	3 %	0.2 %
Low and dense mangrove with mixed <i>Rhizophora mangle</i> and <i>Avicennia germinans</i>	2.8 %	28.5 %	4.6 %
Low and open mangrove with mixed <i>Rhizophora mangle</i> and <i>Avicennia germinans</i>	0.1%	3.7 %	30.7 %
Overall accuracy (%)	85.5 %		

658

659

660 To evaluate the probability of confusion between real change in vegetation cover and seasonal
 661 fluctuation observed by remote sensing, uncertainty bounds were calculated for each class of
 662 zonation. Figure 10 shows the probability of confusion between classes as a function of the
 663 vegetation fraction from linear spectral unmixing. The cumulative frequency curve quantifies
 664 the proportion of the class subject to probable errors as a function of the plant fraction value.



665
 666 **Figure 10:** Probability of confusion between classes according to the values of plant fraction from the linear
 667 spectral unmixing.

668 Red represents ‘High riverine mangrove dominated by *Rhizophora racemosa*’

669 Dark green represents ‘Low and dense mangrove with mixed *Rhizophora mangle* and *Avicennia germinans*’

670 Light green represents ‘Low and open mangrove with mixed *Rhizophora mangle* and *Avicennia germinans*’

671

672 Probable confusion between «High riverine mangrove dominated by *Rhizophora racemosa*» and «Low and
 673 dense mangrove with mixed *Rhizophora mangle* and *Avicennia germinans*»

674 a) Probable confusion between “Low and dense mangroves with mixed *Rhizophora mangle* and *Avicennia*
 675 *germinans*” et “High riverine mangrove dominated by *Rhizophora racemosa*”.

676 b) Probable confusion between “Low and dense mangrove with mixed *Rhizophora mangle* and *Avicennia*
 677 *germinans*” et “Low and open mangrove with mixed *Rhizophora mangle* and *Avicennia germinans*”.

678 c) Probable confusion between “Low and open mangrove with mixed *Rhizophora mangle* and *Avicennia*
 679 *germinans*” et “Low and dense mangrove with mixed *Rhizophora mangle* and *Avicennia germinans*”

680

681 Plant fraction values ranging from 61% to 100% were reliable for assigning to the class ‘High
 682 riverine mangrove dominated by *Rhizophora racemosa*’. Next, the class ‘Low and dense
 683 mangrove with mixed *Rhizophora mangle* and *Avicennia germinans*’ had a plant fraction range
 684 between 38% and 52%, which does not seem to suffer from uncertainties. Finally, values below
 685 33% seem to be reliably assigned to the class ‘Low and open mangrove with mixed *Rhizophora*
 686 *mangle* and *Avicennia germinans*’. For clarity, Table 6 summarizes the uncertainty bounds of
 687 the classes.

688

689 Table 6: Uncertainty intervals for assigning classes over time according to the plant fraction values.

690 The vegetation fraction is expressed here as a percentage.

	Class		
	High riverine mangrove dominated by <i>Rhizophora racemosa</i>	Low and dense mangrove with mixed <i>Rhizophora mangle</i> and <i>Avicennia germinans</i>	Low and open mangrove with mixed <i>Rhizophora mangle</i> and <i>Avicennia germinans</i>
1st Quartile	58	42	29
Median	61	46	33
3rd Quartile	65	50	36
Incertitude	52 % < VF < 61 %	38 % > VF > 51 %	33 % < VF < 38 %

691

692

693 According to these results, the densification of the low mangroves can be reliably interpreted
694 only if the class values cross the threshold of a vegetation fraction higher than 38% (or more).
695 Conversely, the opening of the low mangrove can be reliably interpreted at a threshold of 33%
696 (and below) vegetation fraction. A disturbance in the high shoreline mangrove can be credibly
697 detected only if the values of this class fall below the threshold plant fraction of 52%.
698 Conversely, a recovery can be reliably detected if the values of the low dense mangroves cross
699 the 61% vegetation fraction threshold.

700 **5. Discussion**701 **5.1.Extraction of significant objects for mangrove monitoring**

702 The databases on mangroves in West Africa cover only the surface area. Zonation maps are
703 desirable for guiding conservation strategies (Jia et al., 2018; Wang et al., 2019). However,
704 global or continental databases contain inaccuracies that bias the mapping of plant formations.
705 Here, the differentiation of the mangroves approaches an accuracy of 98.91%, in line with those
706 obtained by Andrieu et al., 2020 and Liu et al., 2021. We aimed to establish a map of mangroves
707 because the quantifications of surfaces in the literature have significant discrepancies.

708 Fent et al. (2019) reported areas of 86 426 ha in 2018 for the same spatial coverage of 30 m.
709 Liu et al. (2021) made their data freely available. For the same spatial extent, in 2017, the extent
710 of areas reached 70 140 ha at 20 m. Andrieu et al. (2020) mentioned a surface area of 63 189
711 ha at 30 m, in 2015, for the mangrove of the Saloum and Joal hydrosystems, but without the
712 mangrove of the Gambia River tributary, which is within the administrative boundaries of
713 Senegal. In this study, we obtained a surface area of 60 988 ha in 2021 at a spatial resolution
714 of 10 m. A cartographic comparison showed that the areas mapped by Liu et al. (2021) were
715 overestimated (Supplementary material). The mapping had inconsistencies; for example, some
716 water channels were mapped as mangroves. However, this mapping was carried out over the
717 entire West Africa, and currently, it is the most accurate database for all West African
718 mangroves at this scale. Furthermore, the areas were likely overestimated by Fent et al. (2019)
719 because the values were widely higher than those estimated by other studies (Andrieu et al.,
720 2020; Liu et al., 2021).

721 Plant formations were mapped on a mangrove mask using the OBIA approach. The vegetation
722 fraction was segmented by linear spectral unmixing. The OBIA approach is preferable for
723 many reasons. First, the vegetation facies of Senegalese mangroves comprise one or more
724 species. Owing to the global biogeography of mangroves (species rich in Southeast Asia but
725 poor in Africa) and the occasionally arid climate, Senegalese mangroves show poor species
726 richness, and are often monospecific in patches larger than a 10m pixel. Li et al. (2019)
727 achieved overall accuracy scores of 83% for species mapping in China. Nevertheless, the
728 species differentiated in this study have their own phenological patterns, which is not the case
729 in the Saloum Delta. Indeed, even in monospecific pixels or objects, spectral contrasts in the
730 time series appear essentially in the average annual trend and phenological patterns.
731 Valderrama-Landeros et al. (2018) achieved scores ranging from 75% to 78% at a specific level
732 and 10 m resolution. Vizcaya-Martínez et al. (2022) achieved accuracy scores between 92 and
733 95% for the classification of species with VIs from S2 images. Using the time series, the authors
734 were able to follow the recovery trajectories of mangrove zoning after disturbance, similar to
735 the zoning presented in this work in Senegal. However, in our case, the upper mangrove was
736 mixed within a pixel, and we did not claim to classify the species. Therefore, working on a
737 plant formation scale is preferable. Transitions between plant formations are noticeable through
738 changes in the relative density of the genera *Rhizophora* and *Avicennia*, and changes in
739 vegetation physiognomy. Therefore, our typology converges with that of Valderrama-Landeros
740 et al. (2021). These authors obtained an overall accuracy of 79% for similar mangroves, both
741 on their specific content and on canopy density variations. Through remote sensing, these
742 transitions are identifiable, and these plant formations are detectable using object-oriented
743 approaches, as demonstrated by Flores De Santiago et al. (2013) and Wang et al. (2018). Plant
744 formations are relevant units for detailed assessment of the impacts of environmental changes
745 on mangroves. Monitoring the fluctuation of zonation over time is challenging, and a typology
746 based on an object-oriented approach would allow for monitoring of plant formations with
747 similar ecological properties. A pixel-based approach could lead to a heterogeneous
748 cartographic result without an ecological context and, therefore, is not interpretable. Moreover,
749 the zoning of the mangrove was unsupervised. Field observations have shown that the species
750 abundance may be heterogenous within an entity equivalent to a pixel. In addition, in most
751 pixels and surveys, one of the three species that were abundant in Saloum was absent. This
752 generates zero inflation, which requires the use of other statistical methods to obtain the
753 relevant pixel-scale information. The OBIA approach circumvents this problem and allows us
754 to work on a scale where a specific mixture constitutes detectable and interpretable facies.

755

756 ***5.2.Relevance of typology***

757 The results show that the approach used in this work allows us to map the zonation of the
758 mangrove only on spectral indices, acting as proxies of cover rate and stand height, but does
759 not allow the extrapolation of information on species abundance for each class. These results
760 are consistent with those of Lymburner et al. (2020), who obtained a three-class typology based
761 on canopy openness (woodland (20-50%), open forest (50-80%), and closed forest (>80%)),
762 using linear spectral unmixing. This typology allowed them to follow evolution over time,
763 which is a future objective of this work.

764 However, our results suggest that the vegetation fraction per LSU is sensitive to mangrove
765 seasonality. Therefore, the index can fluctuate without any changes in the canopy openness.

766 Therefore, following the evolution of classes with a known value amplitude and a quantified
767 uncertainty will allow us to follow the intra-mangrove reorganization by reducing the errors of
768 omissions and commissions of the changes.

769 Valderrama-Landeros et al. (2021) showed that typologies can be affected by mangrove
770 phenology, and that certain dates of image acquisition are more conducive to the development
771 of a reliable typology. In this study, we synthesized the phenological patterns of the classes and
772 quantified the amplitude of their fluctuations over time, given the frequency of spectral
773 similarities between classes during the year (Figure 8). Therefore, assessing changes in the
774 future may be more appropriate, to apprehend signal breaks in the time series metrics of the
775 mangrove rather than establishing a map with the same typology at each date. Indeed, the latter
776 may be distorted by inter-annual climatic variability, which affects the spectral indices
777 (Nicholson, 2013). In addition, Pastor-Guzman et al. (2018) showed that semi-arid mangroves
778 with the same specific composition respond to the onset of the rainy season with a slight
779 phenological delay that affects canopy reflectance values.

780 As was mentioned by Valderrama-Landeros et al. (2021), this could bias the classification of
781 mangrove cover in areas with lower vegetation density. However, these authors showed that
782 the period between the end of the dry season and beginning of the rainy season was the most
783 favorable for producing accurate estimates of mangrove cover in Mexico. Our results indicated
784 a slightly different optimal period. The end of the rainy season and beginning of the dry season
785 showed the strongest contrasts between the classes on raw values and values modelled by
786 harmonic regression. The climatic contexts of the two studies are similar; however, the
787 ‘inverse’ character of Senegalese estuaries greatly influences salinity. A reduction in
788 photosynthetic activity with increasing water salinity (George et al., 2020) or an impact on the
789 seasonality of spectral indices (Celis-Hernandez et al., 2022) have been consistently observed.
790 For Saloum, spectral contrasts appeared to be maximized when species faced lower salinities.
791 Therefore, a typology based on objects that are more sensitive to spatial variations relative to
792 neighboring pixels, rather than to fluctuations in pixel values, can partially overcome the
793 constraints related to the phenology of mangroves mentioned above. Furthermore, the typology
794 presented here and based on the annual phenological pattern allows us to follow the
795 recommendations of Li et al. (2019) and Valderrama-Landeros et al. (2021) who advocate
796 using images over a longer time series to potentially detect possible disturbances. For example,
797 a similar typology has proven suitable for monitoring hurricane damage (Vizcaya-Martínez et
798 al., 2022). Impacts of hydrological changes such as salinity could be monitored at least
799 quarterly. This environmental parameter seems to be a major factor in the spatiotemporal
800 dynamics of the Senegalese mangrove (Andrieu et al., 2020; Descroix et al., 2020; Lombard et
801 al., 2020).

802

803 ***5.3.Perspectives: distinguishing stresses from disturbances***

804 The choice of typology based on a 1-year time series is justified with a view to developing
805 classes that are less sensitive to seasonal fluctuations. When mapping changes in mangrove
806 zonation, we must distinguish between stress and disturbance, which both showed a lasting
807 effect on zonation. The harmonic regression model allowed us to understand seasonal
808 fluctuations and annual trends. Here, we used only the mean of the regression model values to
809 classify the mangrove zonation. The amplitude (seasonal variability), phase (travel time from

810 the origin to the peak of the wave), and RMSE (non-seasonal variability) did not contribute to
811 the robust detection of zonation. Nevertheless, these indicators could be of great importance
812 for understanding the response of mangroves to environmental fluctuations. Celis-Hernandez
813 et al. (2022) captured the impact of physicochemical variables on seasonal fluctuations of
814 mangroves through phenological metrics. Nevertheless, as these authors pointed out, the long-
815 term effects of fluctuations in physicochemical parameters are still poorly understood.
816 Therefore, we suggest that future applications should focus on the impact of climatic variables
817 and salinity on the spatial organization of mangroves at several temporal scales. We also
818 recommend characterizing the impact of these variables and their fluctuations at several scales
819 (spatial and temporal) on the possible threshold effects inducing mangrove dynamics at decadal
820 scales. The use of long-term time series such as Landsat (Bullock et al., 2017; Pirasteh et al.,
821 2021) could provide insights into mangrove responses with this typology over time. In this
822 study, we quantified the uncertainty around plant fraction values to characterize potential
823 changes in mangrove zonation. In the future, we recommend using change detection
824 approaches from temporal segmentations, such as LandTrendR (Kennedy et al., 2010) or
825 CCDC (Zhu and Woodcock, 2014). For example, LandTrendr has been successfully used for
826 mangroves (de Jong et al., 2021). The uncertainty bounds identified in this work allow the
827 parameters to be calibrated in a robust manner to effectively detect zonation changes. As was
828 pointed out by Pasquarella et al. (2022), calibrating the sensitivity of these models to change
829 detection is a key step in mapping land-cover changes.

830 **6. Conclusion**

831 Mapping mangrove zonation is challenging yet important in the management of this ecosystem.
832 Plant formations are organized along environmental gradients, and therefore allow us to
833 approximate the outcome of population dynamics processes that operate at a finer scale. Three
834 homogeneous features were mapped at 10 m spatial resolution from Sentinel-1 and Sentinel-2
835 data. SAR and optical data have proved to be paramount for effective mangrove mapping. The
836 vegetation fraction resulting from a linear spectral unmixing on optical data only allowed us to
837 establish the following clustering: ‘High riverine mangrove dominated by *Rhizophora*
838 *racemosa*’, ‘Low and dense mangrove with mixed *Rhizophora mangle* and *Avicennia*
839 *germinans*’, ‘Low and open mangrove with mixed *Rhizophora mangle* and *Avicennia*
840 *germinans*’. The results of this study show that the average of the values of the plant fraction,
841 obtained by harmonic regressions on each object, allows robust mapping of the zonation of the
842 mangrove on the criteria of canopy cover and height of the stands. In addition, the temporal
843 stability of the typology was assessed. The results indicated that an overall margin of error of
844 14.5% is expected if the plant formations are discriminated against the annual trend of the plant
845 fraction. These acceptable results do not obscure the likelihood of confusion between the
846 classes over time. This leads to probable commission errors and omissions regarding inter-
847 annual zonation changes that must be addressed. Therefore, this study points out that low
848 mangrove classes are most likely to be confused over time. Furthermore, from the perspective
849 of mapping zonation changes on an inter-annual scale, the uncertainty bounds quantified in this
850 study allowed us to estimate that the growth of dense mangrove stands can be reliably captured
851 if the initial values of the low dense mangrove class increase between 16% and 45% for values
852 between the 1st and 3rd quartiles. Conversely, a decrease in the height of the high mangrove
853 stands while maintaining their density can be interpreted if a decrease of 10% to 20% of the
854 vegetation fraction is observed. Second, a densification of the low mangrove canopy can be

855 interpreted if an increase of 13% to 28% in the vegetation fraction values was observed between
856 the 1st and 3rd quartile. Finally, an opening of the low mangrove could be observed if the
857 values of plant fraction of the initially dense mangrove decreased from 21% to 34% between
858 the 1st and 3rd quartile of the class. Therefore, these limits were intended to reliably identify
859 the response of mangrove zonation to environmental changes in the Saloum Delta. The
860 amplitudes of each zonation class identified in this study could allow the characterization and
861 distinction of stresses, disturbances, or recovery thresholds using temporal segmentation
862 methods.

863

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869 **Disclosure statement**

870 The authors declare that they have no known competing financial interests or personal
871 relationships that could have appeared to influence the work reported in this paper.

872 **Data availability statement**

873 Publicly available datasets were analyzed in this study. This data can be found here: The
874 original satellite data from Sentinel-1 and Sentinel-2 are publically accessible from the open
875 cloud platform Google Earth Engine.

876 Sentinel-1 Data Link: [https://developers.google.com/earth-](https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S1_GRD)
877 [engine/datasets/catalog/COPERNICUS_S1_GRD](https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S1_GRD)

878 Sentinel-2 Data Link: [https://developers.google.com/earth-](https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_SR_HARMONIZED)
879 [engine/datasets/catalog/COPERNICUS_S2_SR_HARMONIZED](https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_SR_HARMONIZED)

880 The import of Sentinel-1 and Sentinel-2 data, the calculation of the number of images, the
881 number of cloud-free pixels in the time series, and the harmonic model on the vegetation
882 fraction derived from linear spectral unmixing are available in the following Google Earth
883 Engine code : <https://code.earthengine.google.com/29061ee4b48e419baf491180809e7530>

884 The mangrove extent and zonation data products from this research project can be accessed
885 through the following link: <https://doi.org/10.34847/nkl.c7ecc507>

886 **Supplemental online material**

887 Table: Significance of classes by p-value for the adopted typology based on height, canopy density and
888 presence/absence of plant species.

889 HM: High mangrove – LDM: Low and dense mangrove - LOM: Low and open mangrove

890 a)

Canopy Cover

Class	p-value	p-value adjusted	significance
HM / LDM	0.011	0.021	*
HM / LOM	0.000456	0.001	**
LDM / LOM	0.016	0.021	*

891

892 b)

Height canopy

Class	p-value	p-value adjusted	significance
HM / LDM	0.002	0.005	**

HM / LOM	0.0000138	0.0000414	****
LDM / LOM	0.102	0.102	ns

893

894 c)

*Rhizophora
racemosa*

Class	p-value	p-value adjusted	significance
HM / LDM	0.035	0.071	ns
HM / LOM	0.0000242	0.0000726	****
LDM / LOM	0.096	0.096	ns

d)

*Rhizophora
mangle*

Class	p-value	p-value adjusted	significance
HM / LDM	0.864	1	ns
HM / LOM	0.807	1	ns
LDM / LOM	0.077	0.231	ns

895 e)

*Avicennia
germinans*

Class	p-value	p-value adjusted	significance
HM / LDM	0.045	0.091	ns
HM / LOM	0.004	0.012	*
LDM / LOM	0.332	0.332	ns

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