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Introducing fuzzy set theory to evaluate risk of misclassification of land cover maps to land mapping applications: Testing on coastal watersheds

Zara Teixeira[a,*], Saulo Roberto de Oliveira Vital[b,c,d], Ana Lúcia Vendel[b,d], Juan Diego Lourenço de Mendonça[e], Joana Patrício[a]

[a] MARE - Marine and Environmental Sciences Centre, c/o Department of Life Sciences, Faculty of Sciences and Technology, University of Coimbra, 3004 - 517, Coimbra, Portugal

[b] Centre for Applied Biological and Social Sciences, Paraiba State University, Campus V, Horacio Trajano Street, Cristo Redentor, 58070-450, João Pessoa, Paraiba, Brazil

[c] FAPESQ – Foundation for Research Support of the State of Paraiba, 58.429-690, Paraiba, Brazil

[d] UFPB – Universidade Federal da Paraiba, PRODEMA – Programa Regional de Pós-Graduação em Desenvolvimento e Meio Ambiente, 58.051-970, Paraiba, Brazil

[e] Postgraduate Program in Development and Environment (PRODEMA), Federal University of Paraiba (UFPB), CEP 58051-970, João Pessoa, Paraíba, Brazil

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ABSTRACT

In land cover maps, categories represent a continuum of variation and for this reason, fuzzy set theory, which accepts degrees of membership, has been suggested for land classification. Nevertheless, classical set theory, which only assumes single map categories, is still widely used. The purpose of this study is to develop a methodology to reduce the weakness of land cover maps in which classical theory has been applied. To do so, we propose adding an *error relevance* step after accuracy assessment, which evaluates how relevant are the classification errors to selected land applications. First, a membership matrix is built based on a linguistic scale associated to land cover rates obtained from literature. Then, two fuzzy measures are calculated and the frequency of categories, that do not pose a problem to the user in light of the land application, is determined. The methodology is demonstrated using two Brazilian tropical coastal regions and two land applications relevant for coastal watershed management. The study presents land cover maps of the Mamanguape and the Paraíba estuarine regions, their full accuracy assessment, and the relevance of the classification errors to the land applications.

The accuracy assessment step has demonstrated that the land cover maps are reliable. The error relevance step has shown that the map weakness can be reduced. Both steps show that the land cover maps produced are suitable for further land mapping applications. The results on land cover composition point to the importance of future work focused on the environmental sustainability of the studied regions. The new procedure has proven useful to decrease the degree of distrust with which land cover maps are regarded. The framework provided is suitable for virtually any land mapping application.

1. Introduction

Traditionally, the use of categories in land cover maps has followed classical set theory, in which each location in the landscape is assumed to belong to a single map category, also termed a *crisp set* (Card, 1982; Lewis and Brown, 2001). These assumptions might not be appropriate for land categories that represent a continuum of variation in the landscape and thus the use of fuzzy set theory, in place of classical set theory, has been suggested to reduce the inherent weakness of thematic maps based on *crisp sets* (Gopal and Woodcock, 1994). Despite the wide applications of fuzzy set theory, such as pattern recognition, land evaluation and suitability analysis (Burrough, 1989; Banai, 1993; Altman, 1994), the use of *crisp sets* following classical set theory, is still widely used for category assignment and accuracy assessment of land cover maps (Mollaei and Karamshahi, 2019; Salah et al., 2019; Li et al., 2019). The reasons might have already been advanced by Foody (1999) which stated that the degree to which fuzziness is accommodated will be a function of the nature of data sets, as well as practical constraints faced by the analyst.

Foody (1999) identified three stages in the classification process: i) category definition; ii) category assignment; and iii) accuracy assessment. Fuzzy set theory has been applied to the second and third stage (Foody, 1999). Gopal and Woodcock (1992) developed a methodology suitable for accuracy assessment (third stage) using fuzzy sets, applying

* Corresponding author.
E-mail address: zara.teixeira@uc.pt (Z. Teixeira).

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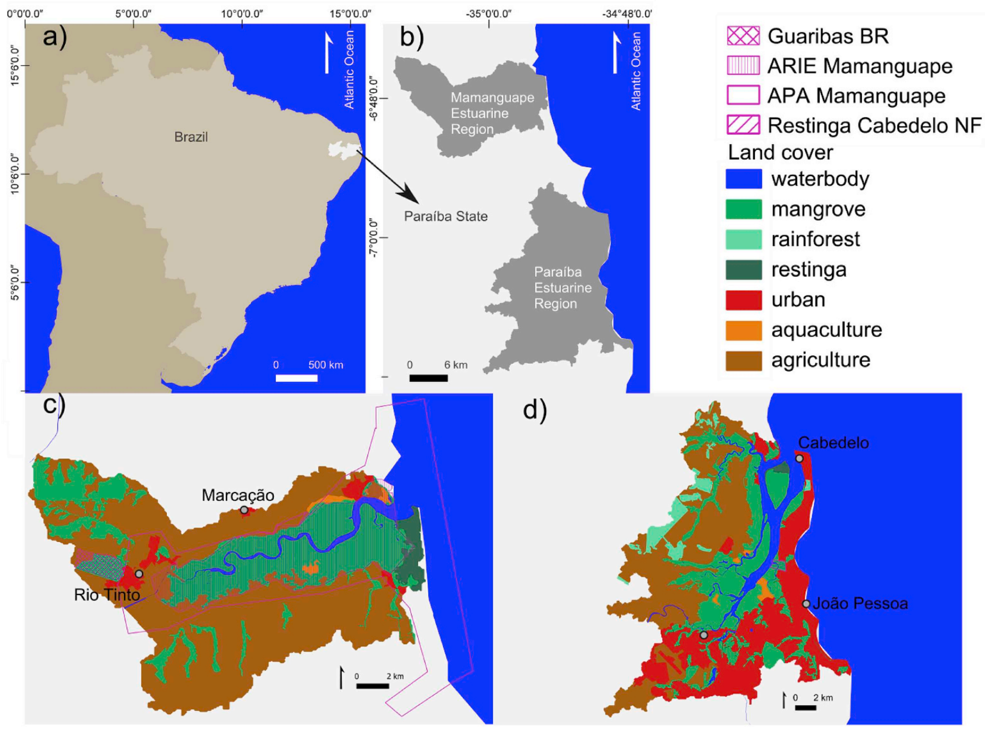

Fig. 1. a) and b) show the location of the study sites. The study sites are the Mamanguape estuarine region and the Paraiba estuarine region, within the Paraíba State in Brazil. c) shows the land cover categories in the Mamanguape estuarine region; d) shows the land cover categories in the Paraíba estuarine region. ARIE-Area of Relevant Ecological Interest; APA-Environmental Protection Area; BR-Biological Reserve; NF-National Forest

a linguistic measurement scale and a group of fuzzy functions. Their goal was to improve the understanding of uncertainty in maps and facilitate improved error modelling. The process relies on experts which evaluate each land use category at each accuracy assessment site and then "choose the most suitable linguistic value to describe his/her perception of the nature of match between each map category and the ground truth".

The purpose of our study is to develop a methodology to reduce the weakness of land cover maps in which classical theory has been used in all three steps. The intent is to use fuzzy set theory concepts in what we could call a fourth stage, in which the relevance of classification errors (determined in the accuracy assessment stage), is evaluated based on the risk of misclassification to selected land mapping applications. The approach relies on the assumptions that the results of land mapping applications are highly dependent on the accuracy of the land cover map used (Castilla and Hay, 2007; Teixeira et al., 2016), and that the accuracy of the land cover map does not affect all land applications in the same manner. For instance, for the quantification of impervious surfaces the accuracy of built up areas is critical (Assis et al., 2016); but to determine wetland losses (Hu et al., 2007) one will be more concerned on the accuracy of the wetland categories, overlooking classification errors between other land categories. The framework provided is suitable for virtually any land mapping application.

The methodology proposed in this paper makes use of the same linguistic membership scale, and two fuzzy functions, proposed by Gopal and Woodcock (1992), and applies them to the traditional confusion matrices derived from classical set theory. However, it differs from Gopal and Woodcock (1992), in four main points: i) expert judgement may be provided by bibliography; ii) expert judgement is applied to each category, and not to each site; iii) the linguistic scale is applied to the estimated area proportions; iv) the results are dependent on land cover mapping applications. Contrary to Gopal and Woodcock (1992) framework, the methodology presented here is less time consuming; is appropriate in the absence of experts supporting the analyst; and can be applied in the absence of raw data sets, as along as a confusion matrix is available, which might be convenient for historic land cover maps.

Our methodology is demonstrated using two Brazilian tropical coastal regions and two land applications relevant for coastal watershed management. The Brazilian tropical estuarine areas are a suitable case study due to the land cover dynamics in the last 500 years. For one hand, they have suffered major changes as a result of severe exploitation of natural resources (Barletta and Costa, 2009), but on the other, more recently, an effort has been put to protect a significant area of such regions (BRASIL, 2011). The observed land cover changes in Brazil (Da Silva et al., 2016; Silva et al., 2018) are relevant to a wide diversity of land mapping applications, such as hydrologic models (Castilla and Hay, 2007; Pontes et al., 2019), water recharge simulations (Galvão et al., 2018; Zomlot et al., 2017), streamflow and sediment projections (da Silva et al., 2018; Shrestha et al., 2018), flood events (Alvarenga et al., 2016; Vafeidis et al., 2019), and forest fires models (Eugenio et al., 2016; Viedma et al., 2017).

2. Tropical estuarine regions from Brazil as case studies

In the coastal area of northeastern Brazil, sugarcane production (Northeast Brazil total, in harvest season 2016/2017, was 44,704t from a total cultivated area of 1×10^6ha; UNICA, 2016), shrimp aquaculture (Roubach et al., 2003) and land reclamation for urbanized areas (Sobreira et al., 2011), have promoted deforestation, soil erosion and aquatic habitats' loss, leading to the impoverishment of aquatic systems (Brockmeyer and Spitzy, 2011; Lacerda, 2006; Sá et al., 2013). To ensure the regulation of human activities within the area surrounding aquatic systems several protection measures have been implemented in Brazilian tropical estuarine regions, aiming to avoid over-exploitation of resources and contamination of water by agricultural run-off, industrial effluents and sewage. Protection measures are regulated by the National Protected Areas System (SNUC - *Sistema Nacional de Unidades de Conservação*) (BRASIL, 2000 Law No 9.985/2000), which has put Brazil as a world leader in the extension of protected areas (BRASIL, 2011). Protected Areas (PA) are a portion of the national territory or territorial waters established by municipal, state or federal government as a delimited area subject to a special regime of administration. PAs are divided in two groups: i) Full protection, which only allow indirect use of their natural resources, save for cases stipulated by legislation; and ii) Sustainable use, which have the goal of making nature

Table 1
Land cover categories, their description and related pressures.

Land cover	Description	Related pressures
Agriculture	Annual and perennial crops.	Areas with moderate to high water consumption. Pollution-generating areas, mainly from diffuse sources.
Aquaculture	Ponds essentially for shrimp farming ventures.	Pollution-generating areas, mainly from point sources.
Urban areas	Consolidated and un-consolidated built-up areas.	Impermeable and pollution-generating areas, namely urban and industrial wastewater, and discharges form from rural, urban and industrial drainage.
Mangrove	Vegetation areas located in the transition environment land to sea, whose flora is adapted to floods and high salinity of water and soil.	Urban occupation, use of charcoal woo, artisanal fishing, overfishing, industrial and domestic wastewater and other residues.
Restinga	Sandbank forest formation occurring in sandy and saline soils with strong marine and fluvial-marine influence.	Infrastructures linked to tourism and commerce (eg. resorts, restaurants), sand extraction.
Rain forest	Dense and thick forest areas.	Wood extraction, hunting
Water body	Water environment.	Industrial and domestic effluents

conservation compatible with sustainable use of resources, reconciling human presence in protected areas (BRASIL, 2011).

The methodology was applied to two northeastern Brazilian tropical estuarine regions with different levels and types of anthropogenic disturbance, the Mamanguape and the Paraíba regions, located in the Paraíba State (Fig. 1).

The Mamanguape region is a low impacted system covering one “Full protection” federal Protected Area (PA) the Guaribas Biological Reserve (4051.62 ha) (BRASIL, 1990. Decree-Law No. 98.884) – and two overlapping sustainable use PAs: the Environmental Protection Area (APA) (BRASIL, 1993. Decree-Law No 924) and the Area of Relevant Ecological Interest (ARIE) of the Mamanguape River (BRASIL, Decree-Law No 91.890, 5AD). Both the APA and the ARIE correspond to IUCN protected area management category V - Protected Landscapes and Seascapes (Ministério do Meio Ambiente, 2007; Shafer, 2015), declared to preserve the welfare of urban populations and improve local ecological condition (Dudley, 2008). According to Brazilian legal framework, APAs are the most permissive PAs in Brazil, potentially exhibiting considerable human occupation, whereas ARIEs exhibit little to no human occupation and are classified due to the extraordinary natural characteristics or the rare regional biota (BRASIL, 2011). In the Mamanguape region the main economic activities with impact on the aquatic ecosystems are associated to shrimp aquaculture and sugarcane production, but other activities, such as tourism, wood extraction and overfishing have also been reported (ICMBio, 2014).

The Paraíba Estuary is a highly impacted system with two Sustainable use PAs: i) the Restinga de Cabedelo National Forest (FLONA), a federal PA with 116.83 ha (ICMBio, 2016); and ii) the Municipal Natural Park of Cabedelo, with 50 ha (BRASIL, 2003). Restinga is a tropical and subtropical coastal forest formation that grows on sandy and nutrient-poor soils, with lower species richness than surrounding rainforests (Cooper et al., 2017; Lima et al., 2011; Valente et al., 2013). The Paraíba estuary is surrounded by a large territory of urban areas and impacted by urban effluents and shrimp production. Extensive sugarcane plantations have almost completely replaced the original tropical forest area and now cover most of the coastal plain sectors in this estuarine area (ICMBio, 2016).

Despite the available qualitative information regarding the human activities in the two above-mentioned regions, a gap exists in the availability of land cover maps with full accuracy assessments that could be used as sources of information for further land mapping applications, such as studying the effectiveness of Protection Areas (Figueroa and Sánchez-Cordero, 2008) or finding relationships between water quality and ecological functioning and adjacent land cover (de Mello et al., 2018; Teixeira et al., 2014). Recent studies have, in fact, revealed, at varying degrees, the pressures and/or impacts from anthropogenic activities in the water quality of the Mamanguape and the Paraíba estuaries, but the role of land cover composition and configuration is yet to be determined. Vendel et al. (2017) found a widespread occurrence of microplastics, while Alves et al. (2016) revealed pressures from nutrient concentrations in estuarine water, showing significantly higher concentrations in the Paraíba than in the Mamanguape estuarine system, particularly during the wet season. Falkenberg et al. (2019) found lower parasite species richness in the most polluted areas, suggesting a disturbance due to lower water quality. Santana et al. (2018), Dolbeth et al. (2016a; 2016b) and Veríssimo et al. (2017) suggest that higher phytoplankton, fish and zooplankton functional diversity might be, to some extent, associated to lower nutrient concentrations; whereas Moura et al. (2016) suggested that the lower feeding quality of zooplankton might be related to anthropogenic disturbance.

3. Methods

3.1. Study sites

Our study sites comprise the subwatersheds directly draining into the Mamanguape and the Paraíba estuaries, as well as the lower coastal areas draining into the ocean. Subwatersheds were defined using the watershed delineation plugin (Moya, 2011) available on MapWindow GIS (version 4.8.6) and were based on SRTM 30 m digital elevation data (version 4.1.) derived from USGS/NASA SRTM data (Jarvis et al., 2008). A threshold of 25 km^2 was used for network delineation.

3.2. Category definition and assignment

Seven land cover categories were defined *a priori* based on expert knowledge, guaranteeing that all types of land cover shared by both regions under study were classified: agriculture, aquaculture, mangrove, restinga, urban, rainforest and water (Table 1).

Land cover mapping was accomplished through visual interpretation, at a scale of 1:10 000, of RapidEye AG imagery at standard processing level 3 A^2 (orthorectified), with 5 m of spatial resolution (ICMBio, 2014). As images from recent years were not freely available, images from June 2011 to December 2011 were used. Although land cover changes may have occurred between 2011 and 2017, land cover persistence tends to dominate most landscapes (Pontius et al., 2004; Angonese and Grau, 2014; Waylen et al., 2014; Teixeira et al., 2014) and thus it was assumed that the images' year would not significantly affect the conclusions of this study.

All vector files were converted to raster with a pixel size of 20 m, in order to account for horizontal tolerance (U.S. Geological Survey, 1998), and the total area occupied by each land cover category was calculated based on the number of pixels. The SIRGAS2000/UTM25S coordinate reference system was used throughout the entire process and spatial analysis was performed using QGIS Valmiera®.

3.3. Accuracy assessment

The accuracy assessment of map classification was based on a location-specific basis using high-resolution historical imagery available on Google Earth (GE) as reference data. Image resolution on GE

Table 2
Mathematical notation for accuracy assessment.

N	Total number of spatial units (pixels)
N	Total sample size
i	Category i
j	Category j
$N_{.i}$	Estimated marginal total number of spatial units of reference category i
$N_{i.}$	Estimated marginal total number of spatial units of map category i
$N_{.j}$	Estimated marginal total number of spatial units of reference category j
$N_{j.}$	Estimated marginal total number of spatial units of map category j
n_{ij}	Number of spatial units of map category i that has reference category j
n_{ii}	Number of spatial units of map category i that has reference category i
n_{jj}	Number of spatial units of map category j that has reference category j
$n_{i.}$	Total number of sample spatial units in map category i (row total)
$n_{.i}$	Total number of sample spatial units in reference category i (column total)
$n_{j.}$	Total number of sample spatial units in map category j (row total)
$n_{.j}$	Total number of sample spatial units in reference category j (column total)
k	Category k
n_{ik}	Number of spatial units of map category i that has reference category k
q	Total number of categories
W_i	Proportion of area mapped as category i
S_i	Standard deviation of stratum i
$S(O')$	Standard error of the estimated overall accuracy
O'	Overall accuracy
U'_i	User's accuracy of category i
P'_j	Producer's accuracy of category j
$S(U'_i)$	Standard error of the estimated **user's** accuracy
$S(P'_j)$	Standard error of the estimated **producer's** accuracy
p'_{ij}	Estimated area proportion mapped as category i that has reference category j
p'_{ii}	Estimated area proportion mapped as category i that has reference category i
p'_{ij}	Estimated area proportion mapped as category j that has reference category j
$p'_{i.}$	Estimated area proportion mapped as category i (row total)
$p'_{.j}$	Estimated area proportion that has reference category j (column total)
$p'_{ik.}$	Estimated area proportions of category k as determined from the reference classification (column total)
V'	Estimated variance
A'_k	Estimated stratified area of category k
A_{tot}	Total area of region of interest (ROI)
$p'_{.k}$	Estimated area proportion that has reference category k (column total)
$S(A'_k)$	Standard error of the estimated area of category k
$S(p'_{.k})$	Standard error of the stratified estimator of proportion of area of category k

depends on the location and source of information. For our study area and for the year 2011, GE provides DigitalGlobe Quickbird imagery with a multispectral resolution up to 2.62 m (Digital Globe, 2005). The analysis comprised two steps: a) accuracy assessment of the classification, and 2) estimation of area and accuracy of the map categories. Because it is impractical to apply accuracy assessment to our total region of interest (ROI), a subset of the total area was sampled.

3.3.1. Sampling design

To select the subset of spatial units (pixels) that would form our baseline for accuracy assessment we applied a stratified random sampling design using the seven map categories as strata. The total sample size (n) for each study region was calculated targeting a standard error for overall accuracy (O)of 0.01 and a user's accuracy (U_i) of 85% (Eq. (1)) (Olofsson et al., 2014). Table 2 presents all mathematical notations.

$$n = \frac{(\sum W_i S_i)^2}{\left((S(O'))^2 + \left(\frac{1}{N}\right)\sum (W_i S_i^2)\right)},\ \text{where } S_i = \sqrt{(U_i(1-U_i))} \tag{1}$$

We determined a total sample size of 1272 pixels for the Mamanguape region and a total sample size of 1273 pixels for the Paraíba region.

For sample allocation to strata, we assigned a minimum of 50 sample units per rare category (FAO, 2016) and the remaining sample units were allocated proportionally to the area of each remaining stratum (Table 3) (Foody, 2008).

Table 3
Sample size, in number of pixels, per land cover category for map validation for the Mamanguape and the Paraiba estuaries.

Land cover		Estuary	
ID	category	Mamanguape	Paraiba
1	agriculture	677	403
2	aquaculture	50	50
3	mangrove	259	269
4	restinga	52	50
5	urban areas	50	352
6	water body	50	99
7	rainforest	134	50

3.3.2. Estimating classification accuracy based on a crisp set

For cross-validation an error matrix for the sample sites was generated, where the land cover category labels allocated by classification of RapidEye imagery were cross-tabulated against the reference data (see Appendix A/Multimedia Component 3 for more detail on the error matrices generated). The error matrix resulting from our sample is reported in terms of estimated area proportions, p'_{ij}(Olofsson et al., 2014). The sample based estimator, p'_{ij}, was calculated according to Eq. (2).

$$p'_{ij} = W_i \frac{n_{ij}}{n_{i.}} \tag{2}$$

To determine the agreement between the reference data and the map classification, i.e. to estimate the accuracy of the classification, we applied a set of measures (Eqs. (3)–(5)) derived from q categories, using the estimated area proportions, which include overall accuracy

$$O' = \sum_{j=1}^{q} p'_{jj} \tag{3}$$

user's accuracy of category i

$$U'_i = \frac{p'_{ii}}{p'_{i.}} \tag{4}$$

and producer's accuracy of category j

$$P'_j = \frac{p'_{jj}}{p'_{.j}} \tag{5}$$

The sampling variability associated with the accuracy estimates was also quantified, reporting standard errors, which were calculated taking the square root of the estimated variances. The estimated variance for overall accuracy is

$$V'(O') = \sum_{i=1}^{q} W_i^2 U'_i(1-U'_i)/(n_{i.}-1) \tag{6}$$

The estimated variance for user's accuracy of map category i is

$$V'(U'_i) = U'_i(1-U'_i)/(n_{i.}-1) \tag{7}$$

The estimated variance for producer's accuracy of reference category $j = k$ is

$$V'(P'_j) = \frac{1}{N'^2_{.j}}\left[\frac{N^2_{j.}(1-P'_j)^2 U'_j(1-U'_j)}{n_{j.}-1} + P'^2_j \sum_{i\neq j}^{q} N^2_{i.}\frac{n_{ij}}{n_{i.}}\left(1-\frac{n_{ij}}{n_{i.}}\right)/(n_{i.}-1)\right] \tag{8}$$

where $N'_{.j} = \sum_{i=1}^{q} \frac{N_{i.}}{n_{i.}} n_{ij}$ is the estimated marginal total number of pixels of reference category j. The 95% confidence intervals were estimated as $\pm z\sqrt{V'(U'_i)}$, where U'_i is replaced by P'_i and O' for the producer's and overall accuracies and where z is the 95 percentile from the standard normal distribution ($z = 1.96$ for a 95% confidence interval).

3.3.3. Estimating area and uncertainty

The estimated area proportions from our sample, p'_{ij}, were used to estimate the area of each land cover category within the total area of our study regions. The stratified area estimate of category k was calculated multiplying the estimated area proportion, $p'_{.k}$, according to the reference data (column total for category k in the error matrix) by the total map area (Eq. (9)).

$$A'_k = p'_{.k} \times A_{tot}, \text{ where } p'_{.k} = \sum_{i=1}^{q} W_i \frac{n_{ik}}{n_i} \tag{9}$$

Area estimation was based on the proportion derived from the reference classification, $p'_{.k}$, and not from the map classification (row total for category k in the error matrix), $p'_{k.}$, because, on premise, the quality of the reference classification is higher.

The standard error of the estimated area of category k was calculated using

$$S(A'_k) = S_{(p'_{.k})} \times A_{tot} \tag{10}$$

where $S_{(p_k)}$ is the standard error of the stratified estimator of proportion of area of category k

$$S_{(p'_{.k})} = \sqrt{\sum_i \frac{W_i p'_{ik} - p'^2_{ik}}{n_{i.} - 1}} \tag{11}$$

where $p'_{ik} = W_i \frac{n_{ik}}{n_{i.}}$ and the summation is over the q categories (column totals). An approximate confidence interval was obtained as $A'_k \pm z \times S(A'_k)$, where $z = 1.96$ for a 95% confidence interval.

3.4. Relevance of classification errors

The relevance of classification errors was established based on the risk of misclassification to selected land mapping applications as perceived by expert judgement. Two land applications were selected for demonstration purposes: i) Water-level attenuation role in the assessment of inundation extents during flood events; and ii) Impervious quantifications for urban watershed management.

A methodology adapted from Gopal and Woodcock (1992) was applied, using a five-point membership scale associated to land cover rates, which can be obtained through bibliographic revision and/or expert judgement (Appendix A/Multimedia Component 2). Once the land cover rates have been set, the differences between rates are calculated (Appendix A/Multimedia Component 2) and used to build the membership matrices for each land application based on a set of linguistic rules (Table 4).

The membership matrices set the risk of misclassification. The land category will pose no risk to the land application when the answer is absolutely right (scale 5), or in other words, when the Map classification and the Reference classification are a match. The land category may pose a low risk (scale 4) to very high risk (scale 1), when the Map classification and the Reference classification are not a match. The membership matrices for the two land applications selected are available on Table 5.

To evaluate how relevant the classification errors of our land cover maps were to each one of the two land applications, two fuzzy measures called MAX and RIGHT, that measure the frequency of matches and mismatches, were used (Woodcock and Gopal, 2000). The estimated area proportions, p'_{ij} were used to quantify MAX and RIGHT. MAX measures a match using the highest rating given to a land category. MAX$_{.j}$ is 1 if $p'jj = p'.j$, otherwise it is 0. The MAX function allows us to answer the question "How frequently do the categories assigned in the map match the categories in the reference?" RIGHT, accepts matches using any degree of right, which in the linguistic scale used here is any score greater than or equal to 3 (Table 4). RIGHT$_{.j}$ is 1 if $\sum_j^q p'_{ij} + p'_{jj} = p'_{.j}$ where p'_{ij} scores are greater than or equal to 3. The RIGHT function allows us to answer the question "How frequently are the categories assigned in the map acceptable, for the specified land application?"

4. Results

The results present the a) land cover maps of the Mamanguape and the Paraíba estuarine regions, b) their accuracy assessment, and c) the relevance of the map classification errors for two land applications pertinent for watershed management.

4.1. Land cover assessment

Considering the study regions as a whole, i.e., not accounting for draining basins or protected areas, agriculture is the dominant land cover category in both the studied regions, and urban plays an important role in the Paraíba region. The Mamanguape is dominated by agriculture (14031 ± 384 ha), mangrove (5528 ± 262 ha) and rainforest (3015 ± 237 ha) (Fig. 2). The Paraíba region is dominated by agriculture (14618 ± 582 ha), urban (9414 ± 470 ha) and mangrove (7842 ± 264 ha) (Fig. 3). The land cover composition differs among draining basins for both regions.

Such results differ when analyzing only the protected areas. Both the Mamanguape and the Paraíba protected areas are dominated by forest categories. In particular, APA and ARIE in the Mamanguape (Fig. 2) and FNCabedelo in the Paraíba (Fig. 3) are dominated by mangrove; whereas RB Guaribas in the Mamanguape (Fig. 2) is dominated by rainforest. Results also show that the three land categories that reveal human occupation (agriculture, urban and aquaculture) are currently present within all the protection areas analyzed (Appendix A/Multimedia Component 3 shows the area (ha) occupied by each land cover class per draining basin and per protected area.).

4.2. Classification accuracy

The results of the classification accuracy based on *crisp sets* demonstrate that the Mamanguape and the Paraíba classified maps are fit to use in subsequent coastal management studies. The Mamanguape River map shows an overall accuracy of 0.904 ± 0.016 (Table 6). The

Table 4
Five-point membership scale. Linguistic values and descriptions adapted from Gopal and Woodcock (1992).

Value	Linguistic value	Description: user point of view	Description: producer point of view
5	Absolutely right	Map and Reference are a match. Perfect	The difference between the land cover rates is 0%
4	Good answer	Would be happy to find this answer given on the map.	The difference between the land cover rates is lower than 10%
3	Reasonable or acceptable answer	Maybe not the best possible answer but it is acceptable; this answer does not pose a problem to the user if it is seen on the map.	The difference between the land cover rates is lower than 40% and higher than 10%;
2	Understandable but wrong	Not a good answer. There is something about the site that makes the answer understandable but there is clearly a better answer. This answer is a problem.	The difference between the land cover rates is lower than 100% and higher than 40%;
1	Absolutely wrong	This answer is absolutely unacceptable and completely wrong.	The difference between the land cover rates is 100%

Table 5
Membership matrices for two land applications.

	agriculture	aquaculture	mangrove	restinga	urban	water	rainforest
Application 1 | Water-level attenuation role in the assessment of inundation extents during flood events							
agriculture	5						
aquaculture	2	5					
mangrove	3	2	5				
restinga	3	2	5	5			
urban	2	1	2	2	5		
water	2	5	2	2	1	5	
rainforest	3	2	5	5	2	2	5
Application 2 | Impervious quantifications for urban watershed management							
agriculture	5						
aquaculture	3	5					
mangrove	3	5	5				
restinga	3	5	5	5			
urban	2	1	1	1	5		
water	3	5	5	5	1	5	
rainforest	3	3	3	3	2	3	5

Paraíba map shows an overall accuracy of 0.886 ± 0.017 (Table 6). In this study, the kappa coefficient was not calculated following the recommendations of several authors (Foody, 1992; Liu et al., 2007; Pontius and Milestones, 2011; Stehman, 1997; Strahler et al., 2006) who discourage its use as it does not serve a useful role in accuracy assessment or area estimation. A unique threshold that defines the acceptable values for accuracy is not available in literature (Anderson et al., 1976; Pringle et al., 2009; Thomlinson et al., 1999), but generally values above 70% are acceptable.

The classifications' actual utility in the field (User accuracy) differs among land categories and between study regions. The lowest user accuracies for the Mamanguape classification were observed for the following land categories: aquaculture, restinga, urban and water, ranging between 68% and 78%, with confidence intervals between 11% and 13%. (Table 6). The lowest user accuracies for the Paraíba classification were observed for the mangrove and urban categories, ranging between 81% and 82%, with confidence intervals lower than 7%, indicating a higher degree of precision of the proportion of pixels mapped in the Paraíba than in the Mamanguape.Both the Mamanguape and the Paraíba classifications predict well all land categories (Producer accuracy), suggesting that a high proportion of pixels observed to be of a given land category in the reference image are correctly mapped to that category (Table 6). Both classified maps show high producer accuracies, greater than 80% with narrow confidence intervals for all land categories, indicating a high proportion of pixels correctly labelled.

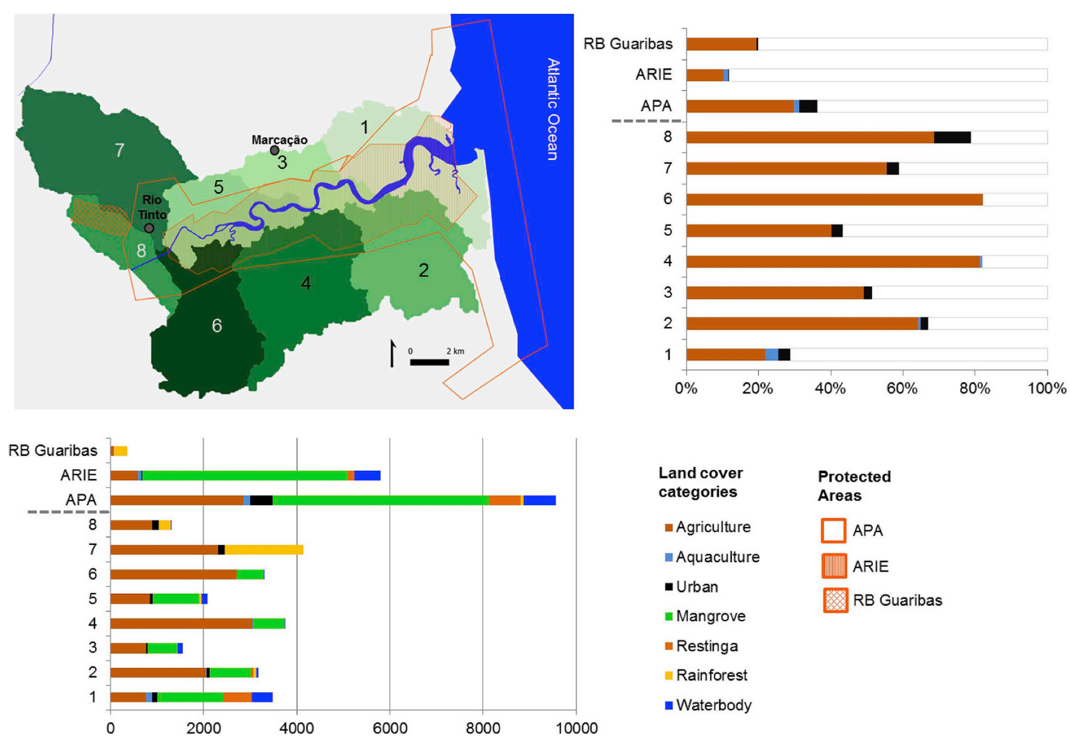

Fig. 2. Land cover mapped area by draining basins and protected areas in the Mamanguape estuary region. The upper left map shows the draining basins and the protected areas within the Mamanguape estuary region. The lower graph shows the land cover mapped area (ha). The upper right graph shows the percentage of land cover pressures by draining basin and protected area. As an example, in draining basin 1, agriculture, urban and aquaculture occupy 993 ha, which corresponds to 28.78% of land cover exerting pressure from this draining basin. Legend: APA - Environmental Protection Area; ARIE - Area of Relevant Ecological Interest; RB – Biological Reserve

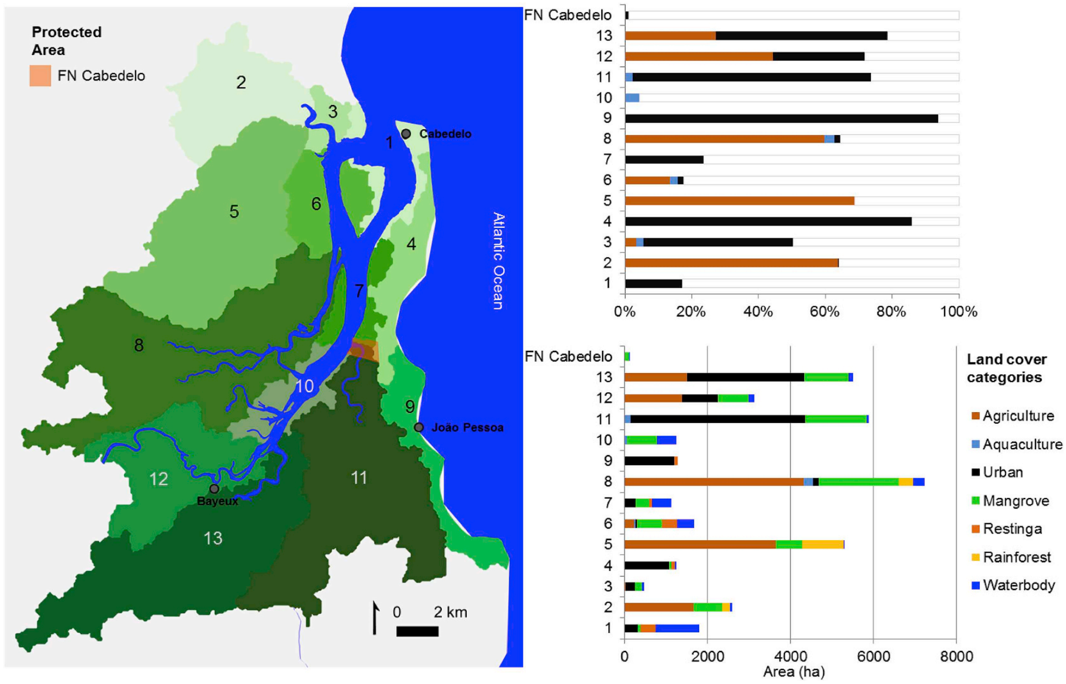

Fig. 3. Land cover mapped area by draining basins and protected areas in the Paraiba estuary region. The left map shows the draining basins and the protected areas within the Paraiba estuary region. The upper right graph shows the percentage of land cover pressures by draining basin and protected area. The lower right graph shows the land cover mapped area (ha). As an example, in draining basin 1, urban is the only land cover exerting pressure, occupying 307.72 ha, which corresponds to 17.17% of land cover exerting pressure from this draining basin. Legend: FN – National Forest

Table 6
Estimated accuracy for the Mamanguape draining basin and for the Paraiba draining basin maps.

	Mamanguape estuary region					Paraiba estuary region				
Overall accuracy										
	O'	$S(O')$	95% CI	Confidence limits		O'	$S(O')$	95% CI	Confidence limits	
	0.904	0.008	0.016	0.888	0.920	0.886	0.009	0.017	0.869	0.903
User's accuracy										
	U'_i	$S(U'_i)$	95% CI	Confidence limits		U'_i	$S(U'_i)$	95% CI	Confidence limits	
agriculture	0.925	0.010	0.020	0.905	0.945	0.950	0.011	0.021	0.929	0.972
aquaculture	0.760	0.061	0.120	0.640	0.880	0.920	0.039	0.076	0.844	0.996
mangrove	0.931	0.016	0.031	0.899	0.962	0.810	0.024	0.047	0.763	0.857
restinga	0.788	0.057	0.112	0.676	0.901	0.920	0.039	0.076	0.844	0.996
urban	0.680	0.067	0.131	0.549	0.811	0.827	0.020	0.040	0.787	0.866
water	0.760	0.061	0.120	0.640	0.880	0.980	0.014	0.028	0.952	1.008
rainforest	0.910	0.025	0.049	0.862	0.959	0.980	0.020	0.039	0.941	1.019
Producer's accuracy										
	P'_j	$S(P'_j)$	95% CI	Confidence limits		P'_j	$S(P'_j)$	95% CI	Confidence limits	
agriculture	0.924	0.00004	0.00008	0.924	0.924	0.828	0.000115	0.000226	0.828	0.828
aquaculture	0.807	0.00001	0.00001	0.807	0.807	0.932	0.000016	0.000031	0.932	0.932
mangrove	0.904	0.00003	0.00006	0.904	0.904	0.880	0.000078	0.000153	0.879	0.880
restinga	0.863	0.00001	0.00002	0.863	0.863	0.825	0.000034	0.000066	0.825	0.825
urban	0.880	0.00001	0.00002	0.880	0.880	0.976	0.000043	0.000085	0.976	0.977
water	0.914	0.00001	0.00002	0.914	0.914	0.896	0.000050	0.000097	0.896	0.896
rainforest	0.835	0.00003	0.00005	0.835	0.835	0.922	0.000031	0.000060	0.922	0.922

O' – Overall accuracy; $S(O')$ – Standard error of the estimated overall accuracy; U'_i – User's accuracy of category i; $S(U'_i)$ - Standard error of the estimated user's accuracy; P'_j – Producer's accuracy of category j; $S(P'_j)$ – Standard error of the estimated producer's accuracy.

4.3. Estimated area and uncertainty

Fig. 4 shows which land cover categories are over- and under-estimated. When the mapped area is higher than the estimated area, and the difference between the two measures is higher than the confidence interval, the category has been overestimated. When the mapped area is lower than the estimated area, and the difference between the two measures, in absolute values, is higher than the confidence interval, the category has been underestimated.

The Mamanguape classification overestimates two out of seven land cover categories beyond the confidence interval - urban and water (green bars with black stripes in Fig. 4) – and underestimates one

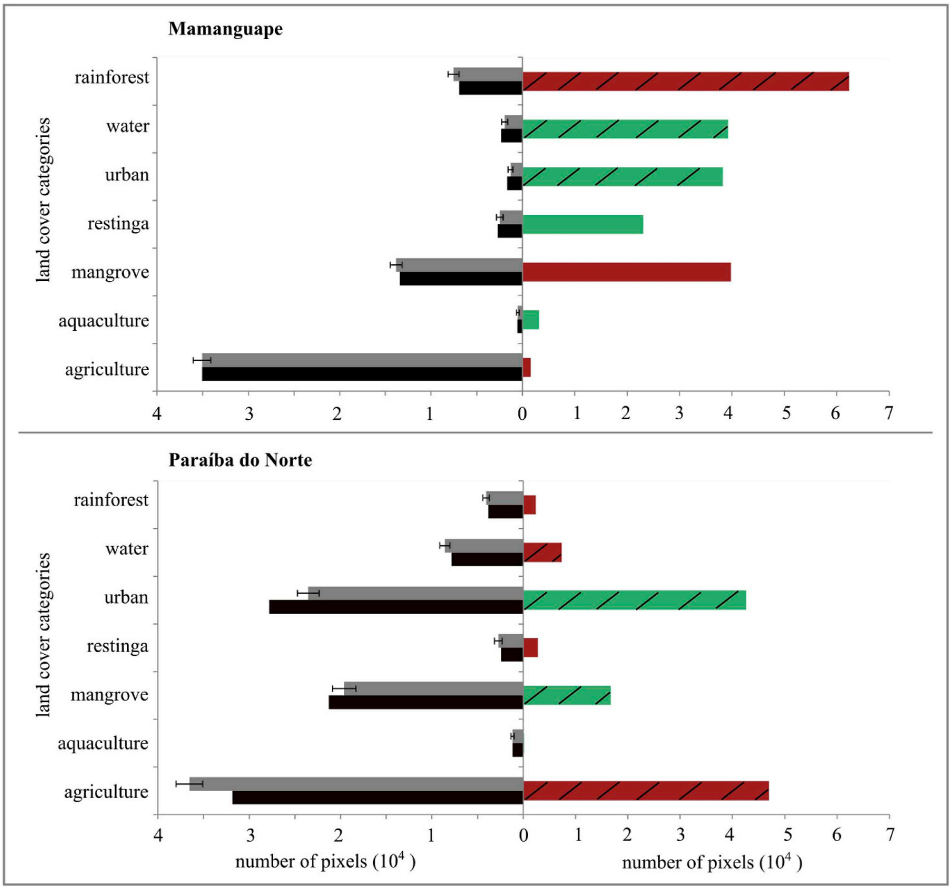

Fig. 4. On the left, grey horizontal bars show the estimated area and its 95% confidence interval and black bars show the mapped area, in number of spatial units. Horizontal bars on the right show the difference, in number of spatial units, between the estimated and the mapped area. Red bars indicate that the classified map underestimates the area occupied by the land cover category. Green bars indicate that the classified map overestimates the area occupied by the land cover category. Black stripes on the red and green bars indicate that the difference between the estimated and the mapped area is higher than the confidence interval calculated for the producer's accuracies

category beyond the confidence interval – rainforest (red bars with black stripes in Fig. 4). The Paraíba classification overestimates two out of seven land cover categories beyond the confidence interval - mangrove and urban – and underestimates two categories beyond the confidence interval – agriculture and water. As an example, in the Mamanguape, 16804 pixels were classified has being urban, but the estimated area points to 12980 pixels, with a confidence interval of 2811 pixels (Appendix A/Multimedia Component 3). Because the difference between the mapped and the estimated, i.e., 3824 pixels, is higher than the 95% confidence interval, we considered that there is a true overestimation of urban.

4.4. Relevance of classification errors

The relevance of the classification errors of both the Mamanguape and the Paraíba land cover maps was evaluated in light of two land application examples: i) Water-level attenuation role in the assessment of inundation extents during flood events in coastal areas; ii) Impervious quantifications for urban watershed management. The results of the "MAX" and "RIGHT" functions are reported on Table 7. Rows indicate the estimated area proportion and the percent of estimated area proportion that are matches using the "MAX" function and the "RIGHT" function.

The best choice ("MAX" function) is equal for all land applications. For the Mamanguape region, the land categories have been assigned the best choice at 90.44% of the estimated area (Table 7), and for the Paraíba Region, the land categories have been assigned the best choice at 98.89% of the estimated area (Table 7).

The RIGHT function differs among land applications depending on the membership matrix built. For the Mamanguape region, the land categories have been assigned an acceptable answer at 97.55% of the estimated area if the map is to be used for the analysis of water-level attenuation role, and 98.89% of the estimated area if the map is to be used for the quantification of impervious surfaces (Table 7). For the Paraíba region, the land categories have been assigned an acceptable answer at 93.52% of the estimated area if the map is to be used for the analysis of water-level attenuation role; and 94.58% of the estimated area if the map is to be used for the quantification of impervious surfaces (Table 7).

The results also show that some land categories show no, or little, room for improvement between the MAX and RIGHT functions. Urban shows 0% improvement for both land applications, on both the Mamanguape and the Paraíba maps. Restinga also shows 0% improvement for both land applications, but only when considering the Paraíba map. Water shows little improvement on both regions if the maps are considered for water-level attenuation assessments, but a definite improvement if the maps are to be used for the analysis of impervious surfaces. The remaining classes show a definite improvement no matter the land application considered, nor the region.

5. Discussion

5.1. Coastal management of case studies

Brazil is concerned with the over-exploitation of resources and thus has policies concerning the regulation of human activities in aquatic systems and surrounding areas (BRASIL, 2000 Law No 9.985/2000). Our results suggest this concern is legitimate. Land cover assessment shows that both the Mamanguape and the Paraíba regions are dominated by agriculture and that urban plays a significant role in the Paraíba region. They also show that the three land categories that reveal human occupation (agriculture, urban and aquaculture) are currently present within all the protection areas analyzed and that the distribution of land cover is unequal among draining basins. If the

Table 7
Results of the MAX and RIGHT functions based on estimated area proportions. Notice the increase in accuracy associated with the use of the less stringent RIGHT function.

	estimated area proportions	MAX		RIGHT		Improvement (R-M)	
		estimated area proportion	%	estimated area proportion	%	estimated area proportion	%
MAMANGUAPE ESTUARINE REGION							
Application 1 | Water-level attenuation role in the assessment of inundation extents during flood events in coastal areas							
agriculture	0.56	0.52	92.42	0.55	97.73	0.03	5.31
aquaculture	0.01	0.01	80.71	0.01	89.85	0.00	9.15
mangrove	0.22	0.20	90.37	0.22	98.99	0.02	8.62
restinga	0.04	0.03	86.26	0.04	90.47	0.00	4.22
urban	0.02	0.02	88.04	0.02	88.04	0.00	0.00
water	0.03	0.03	91.42	0.03	91.98	0.00	0.56
rainforest	0.12	0.10	83.51	0.12	100.00	0.02	16.49
Total	1	0.90	90.44	0.98	97.55	0.07	7.12
Application 2 | Impervious quantifications for urban watershed management							
agriculture	0.56	0.52	92.42	0.55	99.04	0.04	6.62
aquaculture	0.01	0.01	80.71	0.01	100.00	0.00	19.29
mangrove	0.22	0.20	90.37	0.22	100.00	0.02	9.63
restinga	0.04	0.03	86.26	0.04	91.79	0.00	5.54
urban	0.02	0.02	88.04	0.02	88.04	0.00	0.00
water	0.03	0.03	91.42	0.03	100.00	0.00	8.58
rainforest	0.12	0.10	83.51	0.12	100.00	0.02	16.49
Total	1	0.90	90.44	0.99	98.89	0.08	8.45
PARAÍBA ESTUARINE REGION							
Application 1 | Water-level attenuation role in the assessment of inundation extents during flood events in coastal areas							
agriculture	0.38	0.31	82.82	0.35	92.44	0.04	9.61
aquaculture	0.01	0.01	93.24	0.01	100.00	0.00	6.76
mangrove	0.20	0.18	87.95	0.19	91.98	0.01	4.03
restinga	0.03	0.02	82.49	0.02	82.49	0.00	0.00
urban	0.24	0.24	97.65	0.24	97.65	0.00	0.00
water	0.09	0.08	89.57	0.08	89.85	0.00	0.28
rainforest	0.04	0.04	92.20	0.04	100.00	0.00	7.80
Total	1	0.89	88.61	0.94	93.52	0.05	4.91
Application 2 | Impervious quantifications for urban watershed management							
agriculture	0.38	0.31	82.82	0.35	92.65	0.04	9.83
aquaculture	0.01	0.01	93.24	0.01	100.00	0.00	6.76
mangrove	0.20	0.18	87.95	0.19	92.35	0.01	4.39
restinga	0.03	0.02	82.49	0.02	82.49	0.00	0.00
urban	0.24	0.24	97.65	0.24	97.65	0.00	0.00
water	0.09	0.08	89.57	0.09	100.00	0.01	10.43
rainforest	0.04	0.04	92.20	0.04	100.00	0.00	7.80
Total	1	0.89	88.61	0.95	94.58	0.06	5.97

protection policy is to succeed in its goal to regulate human pressures in aquatic systems, then management plans and measures should acknowledge the current area occupied by categories that reveal human presence and the land cover configuration patterns that influence hydrological processes and that might contribute to the environmental quality of coastal systems. Puno et al. (2019), among others (e.g. Arceo et al., 2018; Li et al., 2018a; Li et al., 2018b; Öztürk et al., 2013; Tuomela et al., 2019; Zhang et al., 2012) have shown that urbanization influences the increase in surface runoff, evapotranspiration, and baseflow; whereas the increase of forest vegetation has the opposite impact. Others (León-Muñoz et al., 2013; Records et al., 2014; Schueler et al., 2009; Tang et al., 2011) have shown that land cover and its effects on the hydrological processes have influenced sediment and nutrient loads.

In our study regions, previous studies have shown significant higher nutrient concentrations in the Paraíba, compared to the Mamanguape (Alves et al., 2016), particularly during the wet season. The results of our study show that the Paraíba has an urban occupation considerably higher than the Mamanguape. Considering that urban areas reveal the imperviousness of a region and that impervious surfaces are related to declining water quality (Schueler et al., 2009), to what extent are the differences found by Alves et al. (2016) a result of a higher percentage of impervious surfaces that promote runoff? And how are vegetation patterns contributing to halt runoff (Schueler et al., 2009)? Should management measures re-evaluate land patterns in the Paraíba as a measure to control nutrient concentrations in aquatic systems? Previous studies (Wang et al., 2018; Schueler et al., 2009; Miyata et al., 2019) have found out that land configuration was significantly correlated with nutrient concentrations and infiltration capacity. As such, we consider that further work on land cover configuration (Teixeira and Marques, 2016), rather than land cover composition, could elucidate on those questions. Previous work on the Mamanguape region (Assis et al., 2016) has calculated landscape metrics to evaluate configuration, but focus was solely on the APA Protected Area and no full accuracy assessment of the land cover map produced has been provided. To our knowledge, no similar work exists for the Paraíba region. The accuracy of our land cover maps sustains that they could be used for such land configuration assessments.

5.2. Suitability of classification maps to further land applications

The overall accuracies obtained for the Mamanguape and the

Paraíba maps indicate that both are reliable and that only a few categories are over- or underestimated beyond the confidence intervals. But the degree to which the accuracy of these categories might pose a problem to further land mapping applications, will depend on the overall goal of the application.

Let's take "urban" as an example. The misclassification of urban with any other land category is not acceptable for both the land applications considered. Moreover, because urban has been overestimated, beyond the confidence interval, in both the Mamanguape and the Paraíba maps, the uncertainty of urban might have a significant effect on the final land application results and thus it must be acknowledged and accounted for in further analysis.

Let's take "mangrove" as another example. The misclassification of mangrove with urban, aquaculture and water is not acceptable for the water-level attenuation application and the misclassification of mangrove with urban is not acceptable for the quantification of impervious surfaces. In other words, the classification errors are acceptable if mangrove is misclassified with any other category. In our case, mangrove has been misclassified with agriculture, urban and water in the Paraíba map, the only map that shows an overestimation of mangrove beyond the confidence interval. However, because the misclassification with agriculture is higher than the misclassification with urban and water, which is very low, and the misclassification with agriculture is considered acceptable (Table 5), we have obtained an improvement of more than 4% in the classification accuracy of the mangrove category. As such, the contribution of the uncertainty of mangrove to the final land application results can be considered negligible.

Again, the accuracy of our land cover maps and the improvements acquired after the *error relevance* step, sustain that the Mamanguape and the Paraíba maps could be used for further land mapping applications. In fact, one of the major contributions of this paper is the method that allows us to appropriate land cover maps for application in coastal planning. In our case studies, one of the most important applications would be to track the effect of the protection status. The protected areas in the Mamanguape and the Paraíba regions have been designated for different reasons and the anthropogenic drivers were at different impact levels by the time the protection status was declared. Analyzing land cover changes based on maps with a full accuracy assessment could allow us to determine the effect of the protection status.

5.3. Roadmap challenges

According to Foody (1999) the classification process comprises three steps: category definition, category assignment and accuracy assessment. This study proposes adding a fourth step – *error relevance* - in situations where the classical set theory, as opposed to fuzzy set theory, has been applied throughout the classification process. This new step requires two sub-steps: definition of membership matrix and calculation of fuzzy measures.

The membership matrix is the most challenging issue of the error relevance step since it will depend on the land mapping application considered. For one of the land application examples the land cover rates, used to detect relevant differences in impact among land cover categories, were extracted from previous studies (Vafeidis et al., 2019), but for the other, the land cover rates, though based on previous studies (Boongaling et al., 2018; Booth and Jackson, 1997; Schueler et al., 2009), also relied on expert judgement. For some land mapping applications, the differences among categories might be straightforward. For instance, if one intends to assess the loss of wetlands, then the risk of misclassifying wetlands with any other category is high and the difference between wetland and all other categories, used to build the membership matrix, will be maximum (100%). On the contrary, the risk of misclassification between any other categories is very low and the difference between them will be minimum (0%).

With regard to the calculation of fuzzy measures, the most challenging issue is deciding the "degree of right", i.e., until which score in the linguistic scale used should we accept uncertain answers? The five-point membership scale suggested by Gopal and Woodcock (1992) covers all main five types of possible answers and, unless, there is a strong argument to use a different linguistic scale, we recommend this one. Moreover, in this paper, we considered that any answer with a score greater or equal to 3, i.e., "answers which will not pose a problem to the user", would be acceptable. We consider that this is obvious from a user point of view and thus the same score limit should be used in further assessments.

Finally, we strongly suggest calculating the estimated area and uncertainty of land categories during the accuracy assessment step, as recommended by Olofsson et al. (2014). Such quantifications allow to identify the land categories that are over- and underestimated beyond the confidence interval, providing a mean to identify those categories that might be critical for some land mapping applications.

6. Conclusion

This article introduces an additional procedure based on fuzzy set theory, the *error relevance* step, to deal with land cover maps in which classical theory has been used for both category assignment and accuracy assessment. This extra step is applied after accuracy assessment and evaluates the relevance of classification errors based on the risk of misclassification to selected land mapping applications. The procedure improves the accuracy of the land cover maps produced, decreasing the degree of distrust with which the land cover maps are regarded, by accepting misclassification errors that do not pose a problem to the user in light of the land application. The framework provided is suitable for virtually any land mapping application. The users can compute the error relevance by entering their land cover rates into the *MembershipMatrix* spreadsheet, which they can obtain in the supplementary material (Appendix A/Multimedia Component 1).

From the application of our methodology, the user obtains land cover maps with full accuracy assessments and gains insights regarding the accuracy improvement in face of specific land mapping applications. This study provides land cover maps for the Mamanguape and the Paraíba estuarine regions, delivering, for the first time, reliable maps with full accuracy assessments that are based on hydrologic units, i.e. subwatersheds, rather than administrative regions. Overall, the maps have proven to be suitable for further land applications, but an analysis of the classification errors that might affect selected land applications is still recommended, especially of those land categories that are over- or underestimated beyond confidence intervals. This conclusion stands for any land cover map with acceptable classification errors and all land applications.

The analysis of the land cover composition of the Mamanguape and the Paraíba regions revealed that land categories related to human occupation dominate both regions and are present in all Protected Areas. As such, we consider that the land cover maps produced will be an important asset to support future studies targeting the environmental sustainability of the studied regions, such as evaluating the effectiveness of the protection status in controlling land changes or assessing the relationship between land cover and surface water quality.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ocecoaman.2019.104903.

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