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Image Mining in Remote Sensing for Coastal Wetlands Mapping: from Pixel Based to Object Based Approach

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Abstract. The availably of remote sensing image data is numerous now, and with a large amount of data it makes “knowledge gap” in extraction of selected information, especially coastal wetlands. Coastal wetlands provide ecosystem services essential to people and the environment. The aim of this research is to extract coastal wetlands information from satellite data using pixel based and object based image mining approach. Landsat MSS, Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI images located in Segara Anakan lagoon are selected to represent data at various multi temporal images. The input for image mining are visible and near infrared bands, PCA band, invers PCA bands, mean shift segmentation bands, bare soil index, vegetation index, wetness index, elevation from SRTM and ASTER GDEM, and GLCM (Harralick) or variability texture. There is three methods were applied to extract coastal wetlands using image mining: pixel based - Decision Tree C4.5, pixel based - Back Propagation Neural Network, and object based - Mean Shift segmentation and Decision Tree C4.5. The results show that remote sensing image mining can be used to map coastal wetlands ecosystem. Decision Tree C4.5 can be mapped with highest accuracy (0.75 overall kappa). The availability of remote sensing image mining for mapping coastal wetlands is very important to provide better understanding about their spatiotemporal coastal wetlands dynamics distribution.

1. Introduction

During the last decade, satellite remote sensing imagery has become the source of the most significant recent image database in monitoring the Earth's surface. Image database have diversity in spatial, spectral, and also temporal resolutions. In addition, remote sensing image database is an archive of spatial information that is growing fast enough.Since Landsat-1 was launched in 1972 and operates, this development makes an experience in collecting, processing and analyzing the data around the world. Although such a limitation in the interpretation of information from the database with a large number still remains.Today almost all image processing techniques designed to run on a single recording image and only a few algorithms and techniques to handle multi-time image data [1]. Humans will also experience difficulties and even almost impossible to find information on the knowledge and the underlying pattern in the image when dealing with large data collections. This situation makes the "knowledge gap" in the process of extracting information of digital remote sensing satellite imagery. Knowledge gap arises because it is currently limited image mining techniques and information extraction in large image data sets [2].

Image mining [3], [4] now has a trend and development in framework, technique, level of information, and also applied in the real world. Framework developed into two categories, namely information-oriented [5] and function-oriented. Techniques also developed from object recognition [6], image retrieval and indexing [7], image classification and image clustering [2], association rule mining [8], until the neural network. In addition, level of information developed from the pixel level, object, semantic concept, until the pattern and knowledge [5]. Pixel level is the lowest layer in an image mining system. It is raw image information such as image pixels and a simple image features (color, texture, and shape). Object Level, the focus of the Object level is to identify domain- specific features such as objects and homogeneous regions in the images. Clustering algorithm, along with the domain knowledge can help the image segmentation into several regions/objects.

Field studies of wetlands have been developed since the 1971 Ramsar Convention, because of the importance of wetland ecosystems role in contributing to biodiversity, regulating climate, food sources, sources of water circulation, fishery resources, and medicines for local communities (http://www.ramsar.org accessed April 16, 2016). Wetlands in Indonesia are experiencing pressures toward destruction and deforestation drastically. Degradation rate of about 2 million hectares per year which include illegal logging, forest fires, and large-scale forest conversion such as monoculture oil palm plantations, Industrial Plantation Forest (HTI), mining, and aquaculture shrimp (www.walhi.or.id accessed April 17, 2016). The symptoms of climate change are also influenced by changes that occur in wetlands, with the release of carbon from wetland slash and burn, wetland drying, peat mining, and changes in land use that are not controlled in the wetlands[9].

Due to the importance of wetlands and the growing satellite image database, the aim of this research is to extract coastal wetlands information from satellite data using pixel based and object based image mining approach.

2. Image mining in remote sensing

Image mining is a synergy of data mining technology with image processing to assist analysis and understanding in the image domain [3]. Image mining is also "an interdisciplinary science that includes computer vision, image processing, image retrieval, data mining, machine learning, database and artificial intelligent" [6].

The focus of the image mining is the pattern extraction of image data collection with a large amount. The patterns are in a variety of image mining such as classification patterns, description patterns, correlation patterns, temporal patterns, and spatial patterns [3].

The process of image mining (Figure 1) starts from the image database, followed by pre-processing, transformation and feature extraction, mining, interpretation and evaluation, and discover of knowledge. Digital image processing for Remote Sensing in general has similarity stage with image mining (Figure 1) in pre-processing stage, transformation and extraction of information (features). After transformation and feature extraction, image-mining algorithms will work extracting important pattern to generate knowledge. A series of processes above are called Knowledge Discovery in Image Database[10].

In reality, earth observation data analysis is still performed in a very hard way at the end of continual cycles of trial and error [11]. To overwhelm this, several researches are being managed to introduce several innovative ideas. These are broadly known as knowledge-driven information mining that is based on human-centered concepts, which implements new features and functions allowing improved feature extraction, search on a semantic level, the availability of collected knowledge, interactive knowledge discovery, and new visual user interfaces [12].

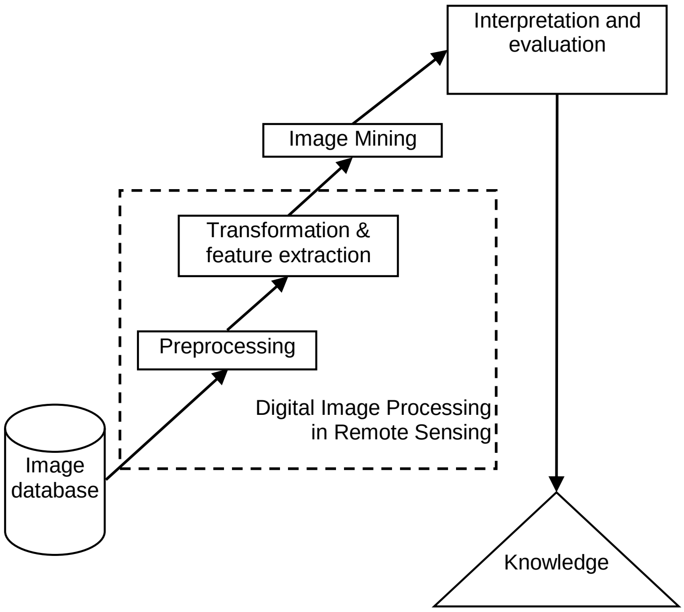

Figure 1. Image Mining Process in Knowledge Discovery related to Remote Sensing Digital Image Processing, modified from [3].

3. Coastal wetlands

Wetlands according to [13] are divided into three components of the ecosystem, namely hydrology, geomorphology, and climate. Hydrology has influence and can change the physiochemical environment, which in turn, along with hydrology, determining the biotic communities found in these wetlands. Overall the forcing functions of wetlands, ecosystem or landscape in this case, including climate, solar energy, temperature patterns, and precipitation. Climate coupled with the landscape geomorphology affect where and when water is long enough then this causes the wetlands that exist.

One of the objects on the earth is water, where two-thirds of the earth is water (sea water). Image mining on water objects will become complex when mixed with land, in this case is an object of wetlands. Wetlands areas under the Ramsar Convention on wetlands are brackish, peat lands and waters; natural or artificial; permanent or temporary; with stagnant or flowing water; fresh, brackish or salt, and including marine areas that depth is not more than six meters at a time low tide. This definition includes the plains of coral reefs and sea grass beds in coastal areas, mud plains, mangrove swamps, estuaries, rivers, freshwater marshes, swamp forests and lakes, and swamps and salty lakes [14]. Wetlands in general by BAKOSURTANAL can be classified as mangrove swamps, estuaries, sea grass, seaweed, coral reefs, lakes, rivers, rice fields and ponds (http://atlasnasional.bakosurtanal.go.id).

4. Materials and methods

The materials and methods described (Figure 2) in this part cover: (a) study area, (b) selection of materials and data, (c) design of field sampling and data collection, (d) transformation and feature (information) extraction from moderate spatial resolution imagery, (e) image mining, and (h) accuracy assessment.

Location of the study area is the Segara Anakan Lagoon (SAL), which is included in the administrative area of Kampung Laut district, Cilacap regency, Central Java province, Indonesia. Kampung Laut sub-district consists of 4 villages, which are Ujung Alang, Ujung Gagak, Panikel and Klaces.

A proportional random sampling pattern applied to collect the wetland data. Proportional based on relief and wetland heterogeneity, the tentative relief map is needed in order to stratify the area and unsupervised classification using k-mean clustering is performed in order to obtain preliminary spectral-related wetland map, from above proportion, location selected randomly.

This study used medium spatial resolution satellite imagery of Landsat MSS (25 April 1978), Landsat 5 TM (5 July 1991), Landsat 7 ETM (22 June 2001), and Landsat 8 OLI (1 May 2014) as primary images and DEM data from SRTM imagery and ASTER GDEM as additional image. Topographic maps (Peta Rupabumi Digital Indonesia) at scale 1:25.000 with 12.5 m contour interval produced by Bakosurtanal (now is Badan Informasi Geospasial) in 2000, covering research area in the Segara Anakan lagoon, Central Java. These included map sheets Kalipucang (1308-241) and Pengolahan (1308-242).

Open-source software for image processing and GIS process used Quantum GIS (with plugin: GRASS, Orfeo Toolbox, and SAGA). Weka - Adams (Algorithm Development and Mining) version 0.4.4, Weka (Java Programming for Machine Learning) version 3.6.0, and Idrisi TerrSet used for image mining process.

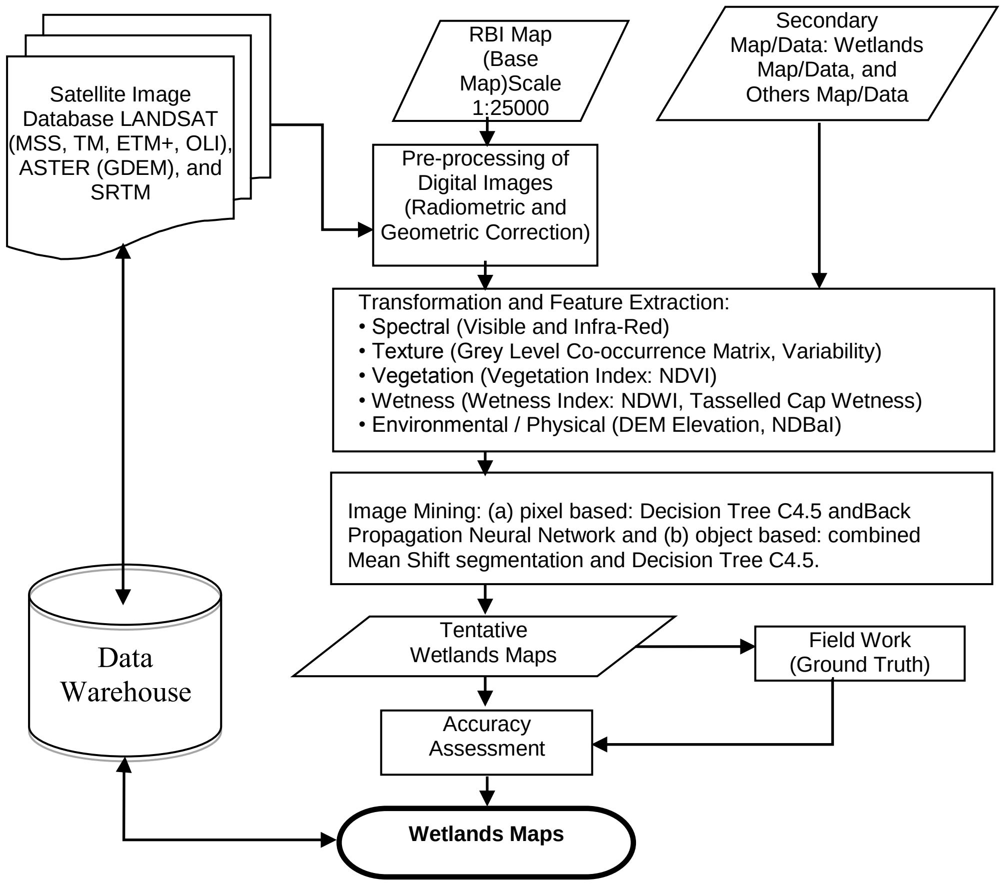

Figure 2. Flow chart of research methods.

Feature extraction and transformation required for image mining input is divided into four sections, namely: (1) The spectral factor, (2) textural factors, (3) factors of vegetation, and (4) physical factors. Spectral factors include spectral channels that exist on Landsat imagery of the MSS, TM, ETM, until the OLI. Texture factors using Haralick (GLCM) texture. Vegetation factors utilizing NDVI as vegetation index derived from the red and infrared channel. Physical factors using elevation values from ASTER image data, and also several indices such as wetness index, and bare soil index. Detailed explanation regarding these factors exists in the following section.

Amount of input bands varies according to the imagery used (Landsat MSS, TM, ETM, or OLI). Landsat MSS used 4 bands, Landsat TM and ETM used 6 bands, and Landsat OLI used 7 bands.

Variations in the input data are divided into spectral channel, vegetation index, wetness index, bare soil index, DEM (elevation), texture, and PCA (Table 1).

Table 1. Input data and the number of bands used in image mining.

No.	Input Data	Quantity	Band Name and Description)*
1.	Landsat 3 MSS, Landsat 5 TM, Landsat 7 ETM, and Landsat 8 OLI	4 to 7	Band 1: Coastal, Band 2: Blue, Band 3: Green, Band 4: Red, Band 5: Near Infrared (NIR), Band 6: Middle Infrared 1, and Band 7: Middle Infrared 2.
2.	Mean Shift image segmentation from Landsat 3 MSS, Landsat 5 TM, Landsat 7 ETM, and Landsat 8 OLI	4 to 7	Band 1: Coastal, Band 2: Blue, Band 3: Green, Band 4: Red, Band 5: Near Infrared (NIR), Band 6: Middle Infrared 1, and Band 7: Middle Infrared 2.
3.	*Inverse* PCA image from Landsat 3 MSS, Landsat 5 TM, Landsat 7 ETM, and Landsat 8 OLI	4 to 7	Band 1: Coastal, Band 2: Blue, Band 3: Green, Band 4: Red, Band 5: Near Infrared (NIR), Band 6: Middle Infrared 1, and Band 7: Middle Infrared 2.
4.	*Bare Soil Index*	1	Band 8: NDBaI
5.	Vegetation Index	1	Band 9: NDVI
6.	*Wetness Index*	1	Band 10: NDWI
7.	ASTER GDEM, and SRTM	1	Band 11: DEM (Elevasi)
8.	GLCM (Harralick) or *Variability* Textures	8 1	Band 12 to Band 19: HT Or Band 12: TexVR
9.	PCA image from Landsat 3 MSS, Landsat 5 TM, Landsat 7 ETM, and Landsat 8 OLI	3 to 5	Band 20 to Band 24 Or Band 13 to Band 17

Note:)* The number of bands used in the image depends on Landsat data (MSS, TM, ETM, or OLI).

Image mining process applied: (a) pixel based: Decision Tree C4.5 and Back Propagation Neural Network and (b) object based: combined Mean Shift segmentation and Decision Tree C4.5.Decision Tree C4.5 used in this study is a non-parametric univariate technique for classifying remotely sensed data. Using training site data, Decision Tree C4.5 in sequence splits the data to form homogenous subsets resulting in a hierarchical tree of decision rules. Three splitting algorithms were used: entropy (information gain), gini, and ratio. Split type is the separation algorithm in form of a decision tree, while pruning (trimming) decision tree is used to trim trees that have been formed. Auto pruning has been done to prune the leaves in the proportion of 1%, 10% and 30%.

Multi-Layer Perceptron (MLP) in this research attempts the classification of remotely sensed imagery through a Multi-Layer Perceptron neural system classifier utilizing the back propagation (BP) calculation. The calculation is based on information from sampling area. MLP also undertake a non-parametric regression analysis between input variables and one dependent variable with the output containing one output neuron, i.e., the predicted memberships[15].

Geographic Object Based Image Analysis (GEOBIA) with mean shift segmentation and decision tree image mining[16] applied to extract coastal wetlands ecosystem map.Image segmentation based on mean shift procedure [17]–[19] is an extension of discontinuity preserving smoothing algorithm. Each pixel is associated with a significant mode of joint density domain located in its neighbor, after the fashions nearby trimmed in generic feature space analysis.

Accuracy assessment of the results of image mining is done by creating confusion between the maps of the image matrix with the data mining field or a reference map that has been recognized truth. Accuracy assessment method used is based on [20]–[22].

5. Results and discussion

5.1. Pixel based: Decision Tree C4.5 and Back Propagation Neural Network (BPNN)

The decision tree C4.5 used input parameters: entropy, gini, ratio, and auto-pruning have a significant influence on the results. Pruning has an influence on the resulting object of detail, the more detailed the object the smaller auto-pruning proportion value, and vice versa. When auto-pruning leaves proportion the greater, then the map seen having a generalization, but it can also be classes that are small in size to be lost because of the class combined with a more dominant class (Figure 3).

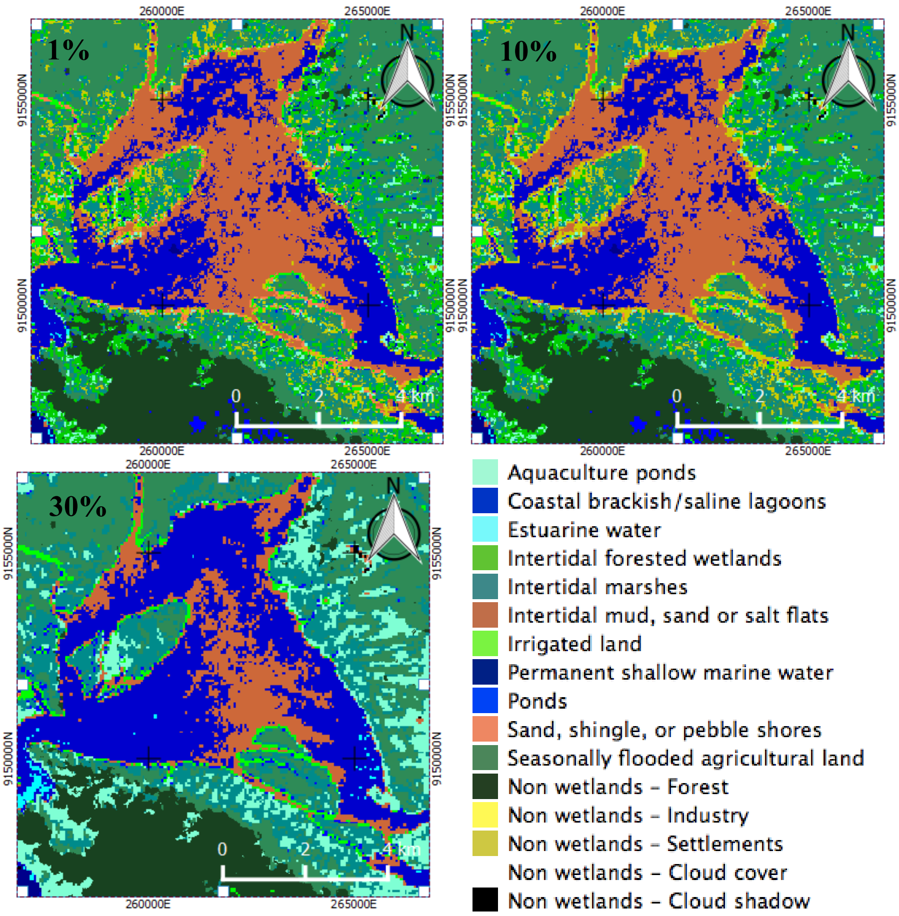

Figure 3. Image mining using Decision Tree C45 with pruning 1%, 10% and 30% of entropy applied to Landsat MSS 1978.The greater pruning the map seen having a generalization.

Entropy, ratio, and gini also have different effect on each application on Landsat imagery in 1978, 1991, 2001 and 2014. Entropy used in decision tree to calculate the homogeneity of a sample, if the sample is completely homogeneous the entropy is zero and if the sample is an equally divided it has entropy of one. Ratio is modification of the information gain (entropy) that reduces its bias towards multi-valued attributes. Gini index of a pure table (consist of single class) is zero because the probability is one. Similar to entropy, gini index also reaches maximum value when all classes in the table have equal probability.

The complexity of a decision tree is usuallymeasured by one of the following: (1) the number of nodes, (2) number of leaf, (3) tree depth and (4) a number of attributes that are used. Therefore, the example simulation on Figure 4 shows a fairly complex decision tree. There issome things are important to know the results of the decision tree: (1) pixels,(2) percentage of pixels, and (3) the purity index. Pixels are the number of pixels in the leaf.Value in percent is the percentage of pixels that are

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included in the total pixels in the class. Purity index on the decision tree is the percentage of correct pixels that really belongs to a certain class in the leaf of the total number of pixels in the leaf. Details of the leaf on the decision tree calculated from the training site data.

Figure 4 show example of the decision tree generated from C4.5 algorithm applied entropy and 30% pruning. There are three setting on pruning: 30%, 10%, and 1% each simulation (entropy, gini, and ratio) with decision tree C45 algorithm.The result from decision tree C45 entropy 30%: number of input attributes 17, number of node 14, number of leaf 15, tree depth 6, and bands applied (9): 1, 2, 5, 7, 13, 15, and 17. Decision tree C45 entropy 10%: number of input attributes 17, number of node 42, number of leaf 43, tree depth 9, and bandsapplied (11): 4, 16, 2, 1, 17, 15, 16, 3, 5, 13 and 7. Decision tree C45 entropy 1%: number of input attributes 17, number of node 59, number of leaf 60, tree depth 13, and bands applied (11): 4, 16, 2, 1, 17, 15, 16, 3, 5, 13 and 7.The higher pruning impact on decreasing the number of node, leaf, depth, and bands applied.

```
+--- Root
+--- Band 4 < 17.5
|         +--- Band 16 < 9.46799993515015
|         |         +--- Band 2 < 13.5
|         |         |         +--- Band 1 < 21.5 Leaf Class 16 [Pixels 4 : 100.00%]   Purity :  75.00%
|         |         |         +--- Band 1 > 21.5 Leaf Class 8 [Pixels 6 :  66.67%]   Purity :  66.67%
|         |         +--- Band 2 > 13.5
|         |                   +--- Band 16 < -0.465999990701675 Leaf Class 3 [Pixels 9 :  70.00%]   Purity :  77.78%
|         |                   +--- Band 16 > -0.465999990701675 Leaf Class 2 [Pixels 16 :  65.00%]   Purity :  81.25%
|         +--- Band 16 > 9.46799993515015
|                   +--- Band 5 < 0.69879999756813 Leaf Class 10 [Pixels 2 :  50.00%]
|                   +--- Band 5 > 0.69879999756813 Leaf Class 6 [Pixels 8 :  60.00%]   Purity :  75.00%
+--- Band 4 > 17.5
          +--- Band 2 < 19
          |         +--- Band 17 < 29.5
          |         |         +--- Band 15 < 46.7690010070801 Leaf Class 1 [Pixels 11 :  60.00%]   Purity :  54.55%
          |         |         +--- Band 15 > 46.7690010070801
          |         |                   +--- Band 13 < 0.352040827274323 Leaf Class 9 [Pixels 5 :  75.00%]   Purity :  60.00%
          |         |                   +--- Band 13 > 0.352040827274323
          |         |                             +--- Band 4 < 38.5 Leaf Class 5 [Pixels 12 :  53.33%]   Purity :  66.67%
          |         |                             +--- Band 4 > 38.5 Leaf Class 11 [Pixels 4 :  33.33%]   Purity :  50.00%
          |         +--- Band 17 > 29.5 Leaf Class 12 [Pixels 6 : 100.00%]   Purity :  83.33%
          +--- Band 2 > 19
                    +--- Band 1 < 33
                    |         +--- Band 7 < -1.2993540763855 Leaf Class 13 [Pixels 1 :  33.33%]
                    |         +--- Band 7 > -1.2993540763855 Leaf Class 7 [Pixels 11 :  91.67%]
                    +--- Band 1 > 33
                              +--- Band 1 < 48 Leaf Class 13 [Pixels 2 :  66.67%]
                              +--- Band 1 > 48 Leaf Class 15 [Pixels 4 : 100.00%]
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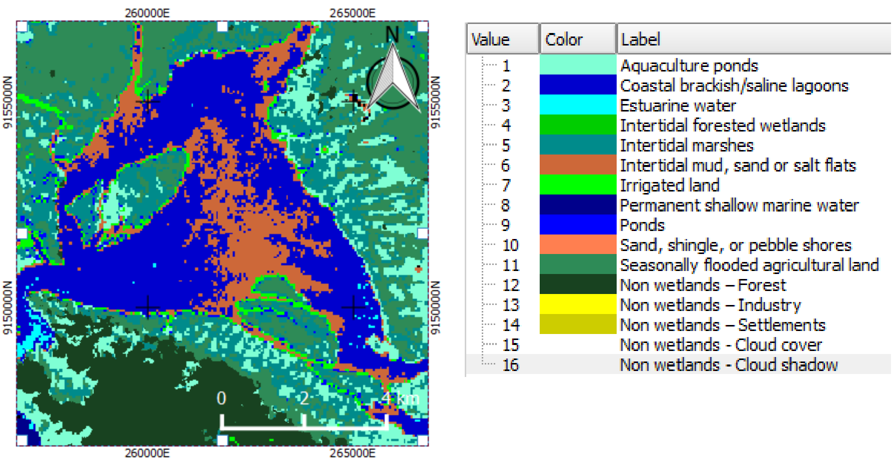

Figure 4. Example of a decision tree is generated from Decision Tree C4.5 image mining algorithm on Landsat 3 MSS 1978 applied entropy and 30% pruning. Result map and legend from this decision tree. Above show leaf class in decision tree equal to value in legend map.

The Back Propagation Neural Network (BPNN) algorithm was run on Landsat satellite image in 1978, 1991, 2001 and 2014 (Figure 5). The setting parameter on BPNN: 17 – 21 inputs, 100000 iterations, 1 hidden layer with 16 nodes, and 16 outputs.The experimental results using algorithms BPNN shows the results of image classification in 1978, 1991, 2001 and 2014 were able to separate the object of vegetation quite well. The object of water body like the coast brackish water / saline lagoon, estuarine water, and the permanent shallow water marine also easy to classify but ponds class look over classified. Objects associated with open land such as intertidal mud, sand or salts flats, and sand, shingle, or pebble shores classified quite well, although the image looks over classified on the image of 1978. Non wetlands object like the class of industry and settlements are more prevalent misclassification in some locations especially on the image of 2001.

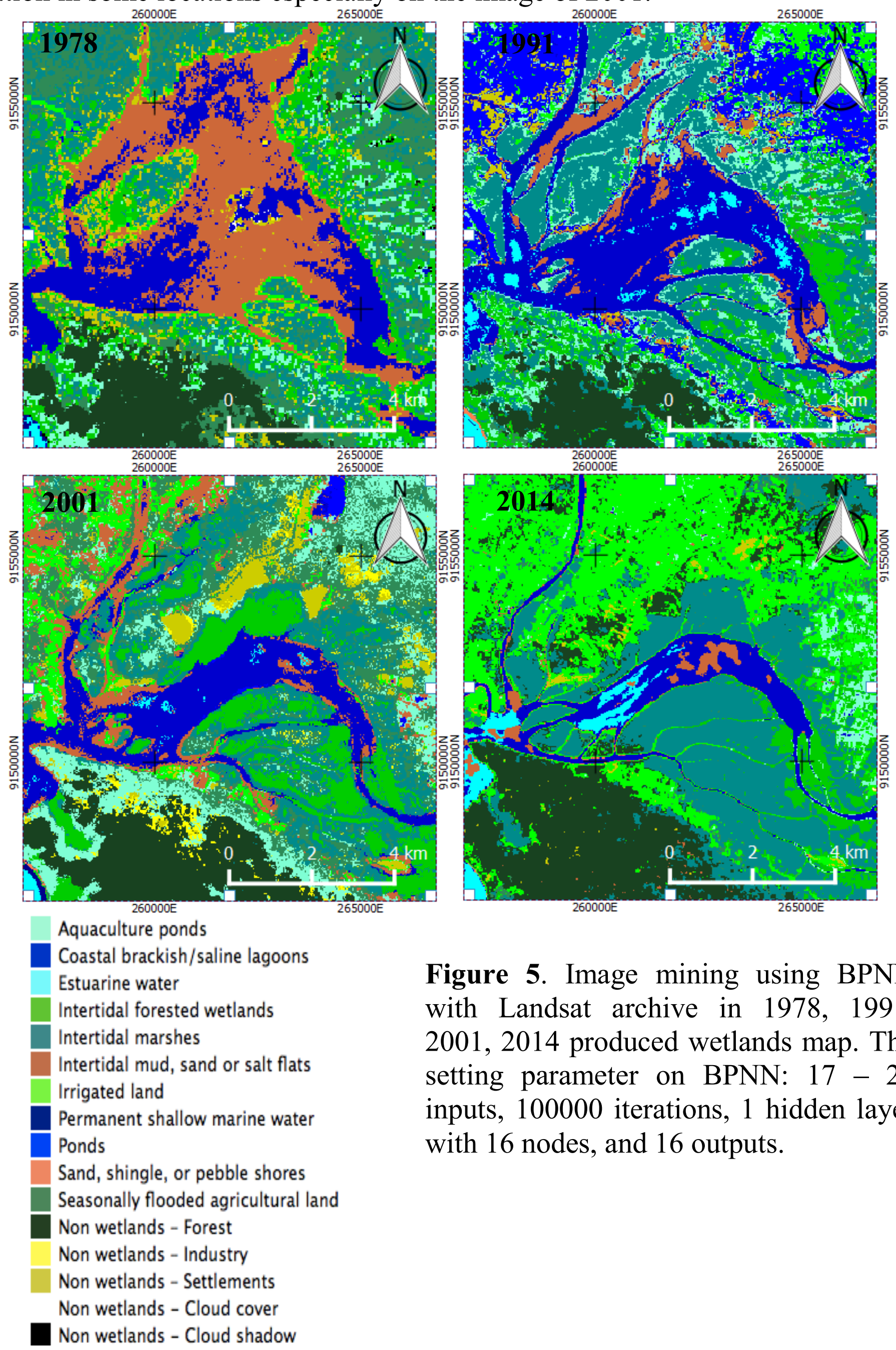

Figure 5. Image mining using BPNN with Landsat archive in 1978, 1991, 2001, 2014 produced wetlands map. The setting parameter on BPNN: 17 – 21 inputs, 100000 iterations, 1 hidden layer with 16 nodes, and 16 outputs.

5.2. Object based: combine Mean Shift segmentation and Decision Ttree C4.5 classification

The results of mining for example in the Landsat OLI image in 2014 using GEOBIA (GEOgraphic-Object-Based Image Analysis) approach, with the first stage is segmentation using Mean Shift clustering algorithm (Figure 6) and the second stage is classification using C4.5 Decision Tree algorithm (Figure 7). Application entropy, gini, and ratio on mean shift image have similarity in delineation result on wetlands class: coastal brackish/saline lagoons seasonally flooded agricultural land, and intertidal mud. Entropy makes the result map too dominate in classifying estuarine water (Figure 7). Gini create the map result quite natural in classifying each class. And ratio built too many irrigated land class.

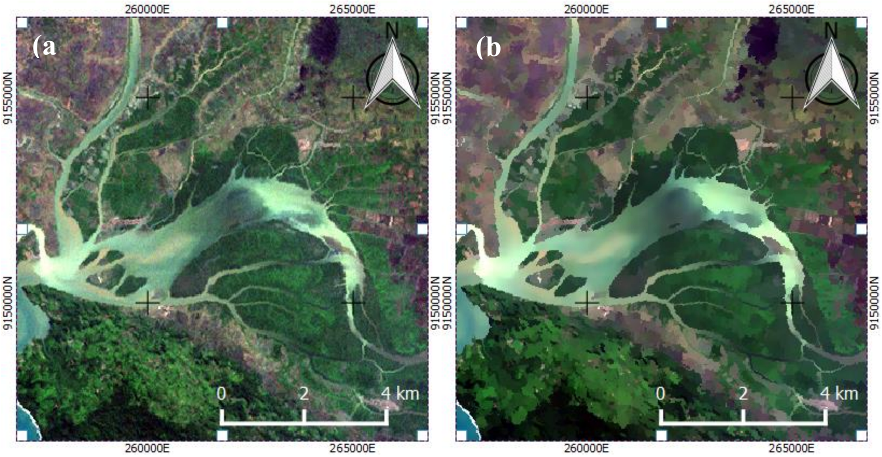

Figure 6. Mean shift filtering is applied in (a) composite Landsat 7 ETM 321 in 2001 to (b) segmenting the image into homogeneous objects.

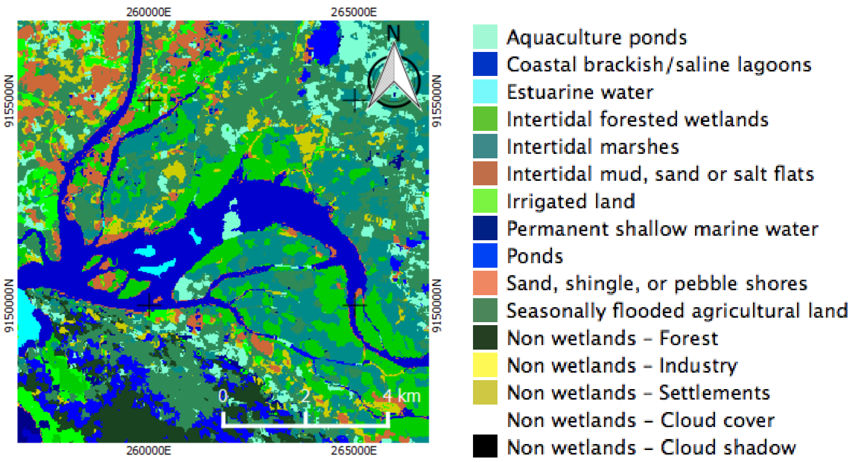

Figure 7. Image mining using Mean Shift and Decision Tree C45 with 1% pruning of entropy applied to Landsat 7 ETM 2001

5.3 Accuracy assessment

Simulation is broadly divided into a simulation using the input value DN (Digital Number) and Spectral Reflectance. Data for training samples are amounted to 140 samples and samples for accuracy test is also the same number (140 samples). Simulation of two large groups, divided into 6 groups with each group there are 76 simulations, so that the total simulation is 456. From the simulation results can be concluded the assessment accuracy on some of the following example (Table 2 and Figure 8).

The accuracy results of the auto-pruning with a proportion of 1% in general have the highest accuracy, followed by the proportion of 10%, and the last with a proportion of 30%. The greater the proportion of pruning makes the results to be generalized on wetland maps. This resulted in the generalization there are several classes of wetlands with small size will be lost and join with the dominant class (the class with greater extents).

The combined input data from DN (Digital Number), inverse PCA and PCA on C4.5 Decision Tree algorithm has the highest overall kappa (0.75). Data cleaning is very influential here, where the value of the inverse PCA and PCA is one way to reduce or eliminate the data that is not as significant as in the input image mining.

Geographic-Object-Based Image Analysis approach does not promise highest accuracy but can increase accuracy. Medium spatial resolution imagery on Landsat imagery (30 meters) has been the object generalizes wetlands, so at this stage of segmentation using Mean Shift clustering to group homogeneity made under segmented image. Objects that minor objects joined with major objects, this applies as majority filter. The decrease in the accuracy of the image mining method is also used due to training area measuring 1 pixel. Training area in future studies supposed to use more than one pixel or using polygons.

Reflectance value has no effect on improving accuracy, precisely DN higher degree of accuracy. DN value is derived from the image of the high-level correction is L1T, with this correction is already an adequate level for coastal wetlands mapping applications.

Table 2. Evaluation of accuracy assessment on the results of mining Landsat image with various algorithms, using 140 samples test accuracy on the data input from DN (Digital Number), inverse PCA and PCA.

No.	**Accuracy Assessment** (*Overall Kappa*)	Landsat MSS (1978)	Landsat TM (1991)	Landsat ETM+ (2001)	Landsat OLI (2014)
	Decision Tree C4.5				
1	Entropy, Pruning 1%	0.539551	0.585049	0.599222	0.750487
2	Entropy, Pruning 10%	0.52666	0.504686	0.625376	0.750487
3	Entropy, Pruning 30%	0.450118	0.496368	0.60115	0.695822
4	Gini, Pruning 1%	0.515382	0.592866	0.607694	0.641465
5	Gini, Pruning 10%	0.507895	0.601324	0.633678	0.656844
6	Gini, Pruning 30%	0.483741	0.542984	0.602862	0.640163
7	Ratio, Pruning 1%	0.500139	0.570195	0.593703	0.665778
8	Ratio, Pruning 10%	0.501973	0.545172	0.603724	0.689303
9	Ratio, Pruning 30%	0.52716	0.591398	0.607448	0.688109
	Mean Shift and Decision Tree C4.5 (GEOBIA)				
11	Entropy, Pruning 1%	0.648261	0.656179	0.692975	0.694631
12	Entropy, Pruning 10%	0.6323	0.648037	0.636477	0.679294
13	Entropy, Pruning 30%	0.557895	0.521286	0.54675	0.63974
14	Gini, Pruning 1%	0.608194	0.633769	0.66606	0.703819
15	Gini, Pruning 10%	0.56206	0.609971	0.600576	0.703291
16	Gini, P.30%	0.53491	0.627521	0.511029	0.624895
17	Ratio, P.1%	0.617806	0.586443	0.683075	0.704132
18	Ratio, P.10%	0.610028	0.586854	0.665934	0.680241
19	Ratio, P.30%	0.589905	0.566259	0.698906	0.686011
	Back Propagation Neural Network (BPNN)				
21	MLP, 100000 iteration	0.527054	0.497544	0.674715	0.64555

Note: the highlight of green color mean the highest accuracy in each column.

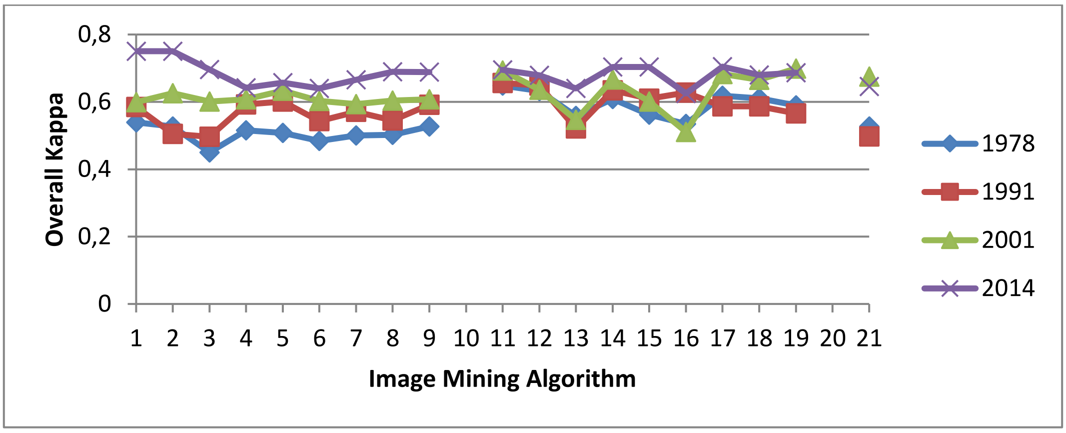

Figure 8. Overall Kappa at various image mining algorithms (Table 2) with the data input from DN (Digital Number), inverse PCA and PCA.

6. Conclusions

Image mining using remote sensing data can be used to map coastal wetlands ecosystem. The combined input data from DN (Digital Number), inverse PCA and PCA on C4.5 Decision Tree algorithm has the highest overall kappa (0.75). The accuracy results of the auto-pruning with a proportion of 1% in general have the highest accuracy, followed by the proportion of 10%, and the last with a proportion of 30%. Geographic-Object-Based Image Analysis approach does not promise increase accuracy in image mining to map coastal wetlands ecosystem. Reflectance value has no effect on improving accuracy, precisely DN (Digital Number) higher degree of accuracy.

This study has recently started image mining for mapping coastal wetlands using temporal Landsat imagery. Knowledge gap of research is still much to be filled, especially the utilization of remote sensing for monitoring coastal wetlands using multiresolution and multitemporal satellite image.

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