Multi-temporal Land Use Mapping of Coastal Wetlands Area using Machine Learning in Google Earth Engine

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Abstract. Coastal wetlands provide ecosystem services essential to people and the environment. Changes in coastal wetlands, especially on land use, are important to monitor by utilizing multi-temporal imagery. The Google Earth Engine (GEE) provides many machine learning algorithms (10 algorithms) that are very useful for extracting land use from imagery. The research objective is to explore machine learning in Google Earth Engine and its accuracy for multi-temporal land use mapping of coastal wetland area. Landsat 3 MSS (1978), Landsat 5 TM (1991), Landsat 7 ETM+ (2001), and Landsat 8 OLI (2014) images located in Segara Anakan lagoon are selected to represent multi-temporal images. The input for machine learning are visible and near infrared bands, PCA band, inverse PCA bands, bare soil index, vegetation index, wetness index, elevation from ASTER GDEM, and GLCM (Haralick) texture, and also polygon samples in 140 locations. There are 10 machine learning algorithms applied to extract coastal wetlands land use from Landsat imagery. The algorithms are Fast Naive Bayes, CART (Classification and Regression Tree), Random Forests, GMO Max Entropy, Perceptron (Multi Class Perceptron), Winnow, Voting SVM, Margin SVM, Pegasos (Primal Estimated sub-GrAdient Solver for Svm), IKPamir (Intersection Kernel Passive Aggressive Method for Information Retrieval, SVM). Machine learning in Google Earth Engine are very helpful in multi-temporal land use mapping, the highest accuracy for land use mapping of coastal wetland is CART with 96.98 % Overall Accuracy using K-Fold Cross Validation (k = 10). GEE is particularly useful for multi-temporal land use mapping with ready used image and classification algorithms, and also very challenging for other applications.

Keywords: land use, machine learning, google earth engine, wetland

1. Introduction
Land use change plays a major role in the study of global change. Land use is a form of human effort to modify the environment into an established environment such as agricultural land, roads, plantations and settlements. Land use can also be defined as "a number of human arrangements, activities, and inputs on a particular land" [1] [2]. Land use / land cover and human / natural modification have largely resulted in deforestation, loss of biodiversity, global warming and increased flood natural disasters [3–5]. Environmental problems are often related to land use change. Therefore, the data available on land use change can provide important inputs for environmental management decision making and future planning [6] [7].

Land use change is not only happened in urban and suburban areas where the changes are dynamic
but also in coastal areas such as in Segara Anakan Lagoon (SAL). Segara Anakan Lagoon is located in the coastal area of Cilacap Regency; this lagoon is surrounded by mangrove forest and muddy land. The lagoon is also surrounded by drains and moats flowing from the mangrove forests, ponds and surrounding rice fields. The existence of this lagoon is strongly influenced by water and sedimentation coming from the Citanduy River and tidal waters of the Indian Ocean through the western slit of Nusakambangan Island and the eastern groove of the Kembangkuning River (Nusakambangan Strait). The river that empties into this lagoon include the river of Citanduy, Kayumati river, Cibereum river, Ujunggalang river and Dangal river, from the rivers the mud is carried away and then will settle in the lagoon. The accumulated sediment then becomes a new land that then gives various impacts, one of which is land use change. The depreciation of the lagoon/waters of Segara Anakan from 185,071.51 Ha in 1978 to 140,693.43 Ha in 1998 and to 123,552.95 Ha in 2003 [8], represents a fairly rapid shrinkage within 25 years. The high sedimentation rate and the formation of new land, accompanied by an increase in the number of people and the level of population demand for food facilities, so that the expansion of the land is closely related to the shrinking of the existing mangrove and bush land forests. Therefore a technology is needed to measure the rate of land use change.

The application of remote sensing technology to environmental conditions monitoring provides optimum benefits and results, since remote sensing provides ease in spatial analysis, spectral analysis, and can cover a relatively wide area with relatively low cost and fast when compared with terrestrial surveys. Briefly, remote sensing data can provide information quickly, objectively, reliably and economically in measurement, mapping, monitoring and use for modelling in land-use change. Remote sensing data to be used in this research activity are Landsat MSS, TM, ETM +, and OLI data.

The technique of remote sensing image classification that developed today is quite diverse, ranging from pixels-oriented to object-oriented. In addition there is a method of classification supervised and unsupervised. The development of satellite imagery is fast enough, triggering the abundance of enough data, while the information generated from the image of the techniques or methods of classification mentioned above less answer the abundance of data. Supervised machine learning algorithm is useful to explore abundant image data, find the hidden relationship between a number of candidate input variables (parameters) with a target or output variable (classification results), so it is very important and one of the solutions in abundance of satellite imagery data and helps in multi-temporal land use mapping of coastal wetlands area. The Google Earth Engine (GEE) provides a cloud based platform for processing large amount of freely available multi-temporal satellite imagery. The GEE also provides a set of the state-of-the-art machine learning classifiers for pixel-based classification that can be used for multi-temporal land use mapping.

The research objective is to explore machine learning in Google Earth Engine and its accuracy for multi-temporal land use mapping of coastal wetland area.

2. Multitemporal Landuse Mapping of Coastal Wetlands Area

Land use can easily be understood as a modification made by humans to the environment into an established environment such as fields, farms and settlements. Land use is defined as "a number of human arrangements, activities, and inputs on a particular land" [1, 2]. The need for land use and the increased of changes have side effects on the emergence of forest reduction, erosion, land degradation, and desert formation.

Detection of land alterations on the surface of the earth, through remote sensing techniques, is a process of detecting changes that apply a number of multi-temporal systems for quantitative analysis, of an event that changes with time function [9]. From the definition it can be concluded that the detection of land use change is the process of identifying different forms of a land use object through observation at different times.

Lu [10], mentioned that in the application of land use change analysis with remote sensing data there are three main stages that influence: (1) image pre-processing including geometric rectification/image registration, radiometric and atmospheric correction, and topographic correction if
area study is in a mountainous region, (2) selection of appropriate change analysis techniques and methods, and (3) the accuracy assessment of the change results.

3. Machine Learning
Machine learning is about programming computers to optimize performance criteria by using data samples or past experiences [11]. Machine learning domains focus on how machines learn the rules of the example. The goal of machine learning is to learn the pattern of the example and then to generalize it with a new example. Kotsiantis [12] divides supervised machine learning into 5 groups: logic based algorithms, perceptron based techniques, statistical learning algorithms, instance-based learning, and support vector machines, and detailed examples are shown in Table 1.

| Supervised Machine Learning | Example |
|-----------------------------|---------|
| Logic based algorithms      | • Decision tree: CART (Classification and Regression Tree) [13], Decision tree C4.5 [14], Random Forests [15], GMO Max Entropy [13, 16] • Learning set of rules [17] |
| Perceptron based technique [18] | • Single layered perceptrons: Winnow [19] • Multilayered perceptrons (Multi class perceptron) [16] • Radial Basis Function (RBF) networks |
| Statistical learning algorithms | • Fast Naive Bayes classifiers [16] • Bayesian Networks [20] |
| Instance-based learning [21] | • Nearest neighbour algorithm [22] • k-Nearest Neighbour (kNN) [23] |
| Support vector machines [24] | • Voting SVM (Support Vector Machines) [13] • Margin SVM [13] • Pegasos (Primal Estimated sub-GrAdient SOlver for Svm) [25] • IKPamir (Intersection Kernel Passive Aggressive Method for Information Retrieval, SVM) [26] |

Note: Example with text **bold** is machine learning in GEE.

4. Materials and methods
The materials and methods described (Figure 1) 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 Landsat imagery, (e) machine learning, 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 (Figure 2). Kampung Laut subdistrict consists of 4 villages, which are Ujung Alang, Ujung Gagak, Panikel and Klaces.
This study used medium spatial resolution satellite imagery of Landsat 3 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 ASTER GDEM as additional image for elevation data. 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 (SAL) and surroundings, Cilacap District, Central Java.
Segara Anakan lagoon, Central Java. These included map sheets Kalipucang (1308-241) and Pengolah (1308-242).

A stratified random sampling pattern has been applied to collect the land use data for ground truth in the field (Figure 3). Stratified based on land use heterogeneity, the tentative land use map is needed in order to stratify the area and create from unsupervised classification. The unsupervised classification using k-mean clustering is performed in order to obtain preliminary spectral-related land use map. From above classification strata, location selected randomly.

Transformation and feature extraction required for machine learning input are divided into four sections, namely: (1) the spectral factor, (2) textural factors, (3) factors of vegetation, and (4) physical factors (Table 2). Spectral factors include spectral channels that exist on Landsat imagery of the MSS, TM, ETM+, and OLI. Texture factors using Haralick (GLCM) texture. Vegetation factors utilizing NDVI as vegetation index derived from the red and infrared channel. Physical factors are using elevation values from ASTER GDEM, and several indices such as wetness index and bare soil index, and also principle component analysis (PCA).

| Land use (coastal wetlands) component | Transformation and Features Extraction |
|--------------------------------------|---------------------------------------|
| Water/Hydro                          | Spectral bands: Blue, Green, and Principle Component Analysis (PCA) |
| • Salinity (fresh water, brackish water, salt water) | Normalize Difference Water Index (NDWI), Modified NDWI |
| • Water Depth < 6 meter               | Tasseled Cap Wetness (TCW) |
| Landuse/Vegetation                   | Spectral bands: Red, Near Infra-Red, and PCA |
| • Tree (Mangrove, Swamp)             | Normalize Difference Vegetation Index (NDVI) |
| • Shrublands (Muddy Swamp)           | Bare Soil Index (BI) |
| • Grass (Brackish Swamp)             | Normalize Difference Bareness Index (NDBaI) |
|                                     | Tasseled Cap Brightness (TCB) |
|                                     | Gray Level Co-occurrence Matrix (GLCM)/Haralick texture (HT) |
| Geomorphology                        | Gray Level Co-occurrence Matrix (GLCM)/Haralick texture (HT) |
| • Basin (close system)               | Digital Elevation Model (DEM) from SRTM and ASTER GDEM |
| • Flow (open system)                 | |

Machine learning in GEE applied 10 algorithms as follows Fast Naive Bayes, CART (Classification and Regression Tree), Random Forests, GMO Max Entropy, Perceptron (Multi Class
Perceptron), Winnow, Voting SVM (Support Vector Machines), Margin SVM, Pegasos (Primal Estimated sub-GrAdient SOlver for Svm), and IKPamir (Intersection Kernel Passive Aggressive Method for Information Retrieval, SVM).

Accuracy assessment of the results of machine learning is done by creating k-fold cross-validation. The original sample is randomly partitioned into k equal sized subsamples (k=10). A single subsample (1 subsample) is retained as the validation data for testing the model, and the remaining k-1 subsamples (9 subsamples) are used as training data; the cross-validation repeated k times (10 times, the folds). The k results from the folds then calculate the averaged to produce a single estimation.

5. Results and discussion

The three set (i1, i2, and i3) of experiments was carried out to select the best combination input and evaluating different machine learning classifiers available in GEE. The first set (i1) of experiment is spectral bands as input for machine learning classifiers. Table 3 show the accuracy assessment of land use classification using 10 machine learning algorithms in Google Earth Engine (GEE). The first set simulation or experiment is to use input from the spectral channel of each image. Landsat 3 MSS uses channels 1, 2, 3, and 4 as inputs. Landsat 5 TM uses channels 1, 2, 3, 4, 5, and 7 as inputs. Landsat 7 ETM+ uses channels 1, 2, 3, 4, and 5 as inputs. Landsat 8 OLI uses channels 1, 2, 3, 4, 5, 6, and 7 as inputs. There are 10 machine learning algorithms on GEE that available to used, and can be grouped into 4 groups. The first group is statistical learning algorithms consisting of Fast Naive Bayes. The second group is a perceptron based technique consisting of Winnow and Perceptron. The third group is logic based algorithms consisting of CART, Random Forests, and GMO Max Entropy. The fourth group is a support vector machine consisting of Voting SVM, Margin SVM, Pegasos, and IKPamir. Highest accuracy is obtained by CART and then Random Forests, both algorithms are logic based algorithms and can also be grouped as decision tree based algorithm. While the lowest accuracy is Pegasos and IKPamir, but both of these algorithms fail to run on the input satellite image.

The second set (i2) of experiment is spectral bands and feature bands as inputs for machine learning classifiers. The feature bands consist of Harralick Texture, NDVI (Normalized Difference Vegetation Index), NDWI ((Normalized Difference Water Index), TCW (Tasseled Cap – Wetness), and ASTER GDEM (Digital Elevation Model). While the third set (i3) of experiment is spectral bands, feature bands, and PCA bands. PCA bands consist of PCA (Principal Component Analysis) and inverse PCA. The highest accuracy is still controlled by CART and Random Forests, just like the first set (i1). But in i2 and i3 there is a SVM group that also has a high accuracy, it’s Voting SVM. The lowest accuracy is still the same that Pegasos and IKPamir both failed to run.

The experimental results of input 1 (i1), input 2 (i2) and input 3 (i3) show that there is an increase of accuracy from i1 to i2 and from i2 to i3, so that the highest accuracy is dominated in the last experiment (i3). It is understandable that in machine learning, more and more features of the identifier will facilitate machine learning algorithms in recognizing objects. Figure 4 shows more detailed graph of accuracy on i3, high accuracy (over 80%) is dominated by CART, Random Forests, and Voting SVM. From several studies, the decision-based machine learning algorithm or generally referred to as logic based algorithms in supervised machine learning, also shows the dominance of high yield accuracy and is quite popularly used [27–29]. In the perceptron algorithm (neural network), the accuracy result is always below 70%. Classification methods using neural networks require considerable amount of sample training to improve the accuracy of the results, the training sample at least 10 times the number of weights in neural networks [30]. Pegasos and IKPamir cannot run well on almost all satellite image data from 1978, 1991, 2001, and 2014, as well as experiments with various combinations of inputs (i1, i2, and i3). When Pegasos and IKPamir are executed there is a warning "Server returned HTTP code: 500" which means something has gone wrong on the web site's server. The Google Earth Engine (GEE) is currently in the testing phase for users, so future expectations will be even better.
Table 3. The accuracy assessment of land use classification using 10 machine learning algorithms in Google Earth Engine (GEE).

| Supervised Classification (Machine Learning) | 1978 i3 | 1981 i3 | 1991 i3 | 1992 i3 | 1993 i3 | 2001 i3 | 2002 i3 | 2003 i3 | 2014 i3 | 2015 i3 | 2016 i3 |
|---------------------------------------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Fast Naive Bayes                             | 27.45   | 35.67   | 59.12   | 38.20   | 42.60   | 48.90   | 49.32   | 43.63   | 50.47   | 63.44   | 63.85   | 58.31   |
| GMO Max Entropy                              | 59.12   | 66.23   | 67.74   | 58.55   | 63.06   | 63.59   | 69.17   | 74.50   | 76.28   | 74.32   | 72.21   | 73.11   |
| Winnrow                                     | 25.85   | 26.35   | 26.85   | 39.45   | 43.13   | 36.83   | 41.59   | 6.69    | 10.24   | 7.25    | 10.78   | 25.18   |
| Perceptron                                  | 31.56   | 47.70   | 50.80   | 43.34   | 52.68   | 53.62   | 52.46   | 8.15    | 54.86   | 53.99   | 53.17   | 60.42   |
| Pegasos                                     | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    |
| CART                                        | 95.59   | 94.09   | 95.39   | 81.74   | 87.93   | 66.85   | 84.12   | 82.34   | 85.89   | 91.34   | 93.78   | 96.98   |
| Random Forests                              | 75.05   | 86.07   | 88.48   | 77.33   | 82.69   | 89.19   | 84.12   | 82.27   | 86.00   | 89.33   | 89.63   | 89.43   |
| IKPamir                                     | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 7.42    | 7.25    | 7.25    | 7.25    |
| Voting SVM                                  | 64.03   | 72.44   | 75.45   | 64.53   | 73.66   | 83.95   | 75.24   | 81.19   | 84.95   | 84.39   | 85.70   | 92.42   |
| Margin SVM                                  | 50.30   | 48.80   | 49.59   | 45.96   | 50.37   | 44.60   | 22.15   | 38.56   | 36.89   | 33.23   | 40.48   | 27.90   |

Notes:
- i1 = spectral bands
- i2 = spectral bands + feature bands
- i3 = spectral bands + feature bands + pca bands

K- Fold (10) Cross-validation in %:

- < 50
- 80 - 90
- > 90

Figure 4. K-Fold Cross Validation (k=10) in % for spectral, feature, and PCA bands input (i3).
Multi-temporal analysis on land use maps is strongly influenced by the results of land use classification accuracy from satellite imagery using machine learning. Land use maps from image classification using CART could be selected because the results are consistently in high accuracy (> 90%). The magnitude change for each land use class is calculated by subtracting the area of coverage from class x in 2nd year with 1st year (Magnitude = magnitude of 2nd year - magnitude of 1st year). In Figure 5, the bottom figure shows the statistical class of land use change from 1978 to 2014, either in Ha or %.

Land use change from 1978 to 2014 is very significant in land use class water bodies, intertidal marshes, and irrigated land. Water bodies and intertidal marshes were reduced by -12.92% and -11.05%, respectively, while the change in irrigated land use was 17.26%. Increased irrigated land shows that human need for land becomes a very important issue in the study of land use change. When observed land use change from 1978 to 1991, 1991 to 2001, and 2001 to 2014 a sequence of land use changes occurred in Segara Anakan lagoon from water bodies to intertidal mud flats, subsequently to intertidal marshes, intertidal forested wetlands and turned into aquaculture ponds, seasonally flooded agricultural land, and irrigated land. Although sometimes not in such sequence, it is understandable that there has been a shift from natural wetlands to artificial wetlands.

High accuracy in land use classification results from satellite imagery sometime is not necessarily suitable for analysis of land use change. The accuracy test uses only samples, high accuracy only in the sample locations representing the population. For example in the 1978, the area of settlements land use class are 6648.21 Ha and reduced (-) by 5134.5 Ha to become 1513.71 Ha in 2014. It is illogical, in the case of such a widespread reduction in settlement land use. Analysis of land use change needs to take into account that there are several classes of land use that have low accuracy and are quite difficult to distinguish from other classes. The conditions at the time of satellite image recording should also be noted, whether the climate conditions are the same or not in any multi-temporal image to be analyzed. If the image recorded in the rainy season would be different classification results when compared with the image recorded in the dry season. The 1978 Landsat image was recorded in April and Landsat's image of 2014 was recorded in May, although the moon is close together, checking on climate conditions is essential.

When returning to the goal of machine learning that is learning the pattern of the example and then able to generalize it with a new example, then the accuracy of the above is enough to see the difference in the accuracy of each machine learning performance. If it continues to the process of analysis of land use change, it should be noted that some things as mentioned above are climatic conditions when recording multi-temporal images and more samples to help machine learning to recognize objects better. In addition, the number of land use classes should not be too much and focus on a study, e.g. land use change from non-urban to urban, agriculture to non-agriculture, natural wetland changes to artificial wetlands. The simplification of land use into two classes did to make it easier to see the common threads of land use changes. The simplification of the changed object entity refers to "finding simplicity in complexity" [31] and the land use change conceptual model [32, 33]. The method of updating land use map manually using visual interpretations of satellite imagery or semi-automatic updating land use map using image segmentation, GIS analysis, and visual interpretation could be selected if the area of study is not extensive [34]. GEE is particularly useful for multi-temporal land use mapping with ready used image and classification algorithms (machine learning) and also very challenging for other applications.
Figure 5. Land use map in 2014 extract from Landsat 8 OLI using CART machine learning. The legend has shown the statistics of each land use class and the changes from 1978 to 2014. Detail maps in a square box shown in Figure 6 (next figure).
Legend:

| Land use class                  | Class color |
|---------------------------------|-------------|
| Aquaculture ponds (1)           |             |
| Water body (J)                  |             |
| Intertidal forested wetlands (I)|             |
| Intertidal marshes (H)          |             |
| Intertidal mud, sand or salt flats (G) |         |
| Irrigated land (3)              |             |
| Ponds (2)                       |             |

Figure 6. Land use map in 1978 to 2014 extract from Landsat imagery using CART machine learning.
6. Conclusions
Machine learning in Google Earth Engine are very helpful in multi-temporal land use mapping, the highest accuracy for land use mapping of coastal wetland is CART (96.98 % Overall Accuracy). Some of machine learning is not stable (GMO Max Entropy and Pegasos); it’s still in testing status. If it is to be used for the analysis of land use change, it is necessary to check the climatic conditions at the time of recording of each multi-temporal image, and need to focus on what land use changes will be assessed. The simplification of land use into two classes did to make it easier to see the common threads of land use changes. GEE is particularly useful for multi-temporal land use mapping with ready used image and classification algorithms (machine learning) and also very challenging for other applications.

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