An object based approach for classifying the Vietnamese Mekong Delta with the random forest algorithm

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Abstract

The Vietnamese Mekong Delta rapidly became an area of interest, since land usage changed fast. A consistent land use time series had been produced by Minderhoud et al. (2018) from 1988 to 2009 while making use of object based analysis and the random forest algorithm. No new land use classification has been made since. The aim of this study is to classify a more recent image while making use of the same methods as Minderhoud et al. (ibid.). The overall accuracy of the classified image is above the 80%, which can be considered good. The methods of (ibid.) are reproducible, but the final map cannot be compared to their land use time series.

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1 Introduction

Land use in the Vietnamese Mekong Delta changed rapidly over the past decades. The current land use situation is characterized by small mangrove strips along the coast with aquaculture behind it. More inland, extensive agricultural areas with mainly rice and orchards close to the main rivers are observed (Coumou 2017). The Mekong Delta follows the general Southeast Asian trends, which means that the total area of urban, aquaculture and rice cropping increased while deforestation occurred (ibid.). The prominent and characteristic land-use sequences that reflect the developments in the delta are: cultivation of previously undeveloped land, changes in agricultural practice, and urbanization (Minderhoud et al. 2018). One of the examples of conversion of agriculture is the increase in coverage by rice. The total area of rice showed an increase of 1255 km^2 (over 3% of the delta area) between 2001 and 2012 (Coumou 2017). Locally, the area of rice cropping increased from less than 50% of the area before the eighties to about 90% in 2005 (ibid.). A special area of interest is the province of Tien Giang. Since this province is the main passage of the Southern part of the Mekong Delta to Ho Chi Minh City, it is expected that there is more urbanization seen and more land conversion to other agricultural practices. There is, however, not a lot of recent data available about the land use change in the Mekong Delta. The Vietnamese government produces land use maps every five years, however, they are not publicly accessible and, if available, lack metadata on data sources and used methods (Minderhoud et al. 2018). There are many past land-use maps available, but they vary in terms of subject. (ibid.) made a consistent land use time series of the Mekong Delta from 1988 to 2009. The main question is: How did land use change in the Mekong Delta since 2009? The aim is to add data to the existing land use time series of Minderhoud et al. (2018).

Minderhoud et al. (ibid.) selected four images taken by Landsat TM 5 with limited cloud cover acquired during the dry season (January – March, but preferably in February) in 1988, 1996, 2006 and 2009 to enable distinction of dry-season irrigation. They used Object Based Image Analysis (OBIA) in the same way as Addink, Van Coillie, and Jong (2012). OBIA does not only look at spectral information, but also at shape and context characteristics for the classification (Minderhoud et al. 2018; Addink, Van Coillie, and Jong 2012). An example of OBIA mentioned by Blaschke (2010): "A shrimp pond and a canal both have the spectral properties of water. However, with OBIA they can be distinguished based on their shape, e.g. rectangular versus a line. As a result, OBIA generally performs better than pixel-based approaches, especially with high-resolution imagery." For classifying the image, Minderhoud et al. (2018) made use of the Random Forests algorithm. The trained random forest was subsequently used to classify all objects of the image based on their spectral and spatial characteristics. For this study, Landsat 8 will be used, since Landsat 5 was disabled in November 2012. Can the object-based classification method of Minderhoud et al. (ibid.) be applied to Landsat8 images?

2 Methods

2.1 Software

The pre-processing and the cloud masking has been done in Google Earth Engine. This program has easy to use code to mask clouds. These results were exported as geoTIFF and were then used in eCognition. The images provided in GEE are not in common pixel values, but are supplied in scale factors.

2.2 Classification

To make the classification, there will be made use of different bands and band ratios/indices such as normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI). Firstly, the objects will be generated while making use of the different bands and indices. Secondly, the training areas will manually be selected from differences in spectral and spatial features. Finally, the random forest algorithm will use the training areas to classify the whole satellite image. There was chosen for this method since it is the most similar compared to the method performed in (Minderhoud et al. 2018)

The spatial and spectral characteristics of the land use classes will briefly be described below, for a more detailed description, see (Coumou 2017). The different categories and their division into classes are stated. These categories are based on (Minderhoud et al. 2018), but some are not exactly similar.

Aquaculture. Aquaculture consists of mostly shrimp farms, but also of fish farms which are concentrated close to the sea. Structured geometric patterns, small dikes at the border with a rectangular strip of rows of mangrove trees which are surrounded by the water of the actual shrimp pond. Aquaculture has a relatively low reflectance in all spectral bands.

Agriculture. Crops have different growing stadiums. During the first weeks, the surface characteristics dominate the reflectance. In this weeks, the values of vegetation indices EVI & NDVI are still very low. The NIR is only slightly lower than the reflectance in the visible spectrum (VI) (Nguyen et al. 2012; Kuenzer and Knauer 2013) After 12 weeks, NDVI, EVI and NIR reach their maximum and Vi reflectance reaches minimum. After the plants matured phase, it becomes yellowish and the reflectance decreases; EVI & NDVI lower. If SWIR is used, the accuracy of classifying rice increases (Kuenzer and Knauer 2013)

Agriculture is divided in three classes. The **triple crop rice / double crop irrigated rice** can be distinguished based on the high peak in the vegetation indices. As can be seen in figure 1, the spectral signature of EVI of triple crop/double crop irrigated rice is high in dry season. This peak is not only a peak over time, but also spatially compared to other classes. Besides, the shape of the fields surrounded by generally bare dikes is characteristic. The timing of the dry-season crop peak varies spatially, because the start of the rice cycle depends on the local water distribution scheme (ibid.). The **bare fields in dry season / rain fed rice** form another subclass. The absence of vegetation in the satellite images results in low EVI values, negative NDVI values, a bright appearance in true and false color images and a much higher SWIR1 and SWIR2 reflection than most other classes if the soil is dry. If the soil is wet, the reflectance is significantly lower. As can be seen in figure 1, single and double crop rain fed rice have a relatively low EVI values in dry season.

The last agriculture subclass is **other crops**, which contains all crops other than rice. Generally, this class has a lower NIR reflection and hence lower vegetation indices than rice. Besides, the fields seem to be smaller and the spectral difference between fields is larger compared to rice (Coumou 2017).

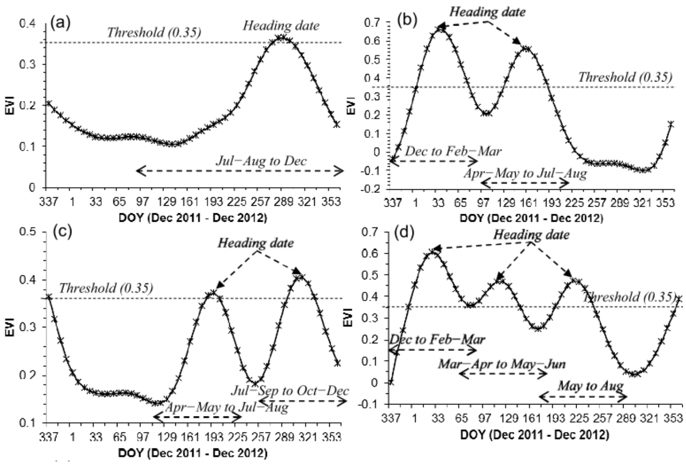

Figure 1: The spectral signatures of EVI of different types of rice in the Mekong Delta by Son et al. (2013): (a) single-cropped rain-fed rice, (b) double-cropped irrigated rice, (c) double-cropped rain-fed rice and (d) triple-cropped irrigated rice.

Forest. The category forest is divided into three classes. The first one is **mangroves, natural forest**. There is little natural forest left in the Mekong Delta, however, mangroves can be found near the shore. Mangroves can be discriminated from other vegetated classes by its lower NIR reflectance than e.g. rice and compared to the other inland LU classes, they have relatively low SWIR1 and SWIR2 reflectance values (Kuenzer, Bluemel, et al. 2011). Besides, their shape is quite circular. The second class is **orchards**. This class comprises the orchards of fruit gardens and pineapple plants, which form the dominant LU close to the main river branches. However, in this case its NIR reflectance and herewith vegetation indices values are in between those of dry-season rice and plantations (ibid.). Additionally, the spectral variation within a patch of this class is slightly larger than for a dry-season rice patch (Coumou 2017). The third class is **plantations**. These plantations can be found in the centre of the Mekong Delta. They have a lower NIR and EVI reflectance compared to orchards and they have a distinct square shape.

Urban. The category urban is divided into four classes. **Urban Dense** corresponds to cities with many buildings close to each other and little vegetation. **Urban open** corresponds to the periphery of cities and other areas with many buildings combined with vegetation. **Industry** corresponds to a block of buildings, relatively close to each other. This can be separated from other urban classes by their shape, industrial areas are more rectangular. **Linear features** corresponds to dikes and roads with some buildings and gardens along it (ibid.).

Water. Water has the lowest NIR, SWIR1, SWIR2, EVI and NDVI values of all classes except aquaculture (ibid.).

Clouds. The class clouds is represented as no data in the final map. The clouds were masked during the pre-processing in GEE. They are recognizable as values below zero. Some smaller clouds are still present in the image.

2.3 Random Forests

Random forests is a machine learning technique that uses an ensemble of decision trees to predict Y using multiple X-variables. In this case, Y is class and X-variables are the several spatial and spectral characteristics. Random Forests is not often used in remote sensing, though it can give high classification accuracies (Gislason, Benediktsson, and Sveinsson 2006). The RF has to be created first using a training data set which contains values for the X-variables and the corresponding Y-values. Each tree is automatically built by repeatedly splitting the training data based on the best threshold of one of the X-variables. The best splitting rule at each decision tree node is determined by the algorithm using a random sample of the X-variables (Coumou 2017; Breiman 2001). The second step is to apply the RF. All non-training data points for which the X-values are known are put into all trees (Breiman 2001). They follow a path determined by their X-values and the splitting rules. Each final node corresponds to a y-value, which in this case is a classification. Each outcome is compared with the known Y- value, giving an error rate (classification) or mean squared error (MSE) (regression) per tree. In case of classification, for extra accuracy, a set of validation samples could be used. This validation set can be used to test the accuracy of the random forest algorithm. For more information about random forest, see (ibid.).

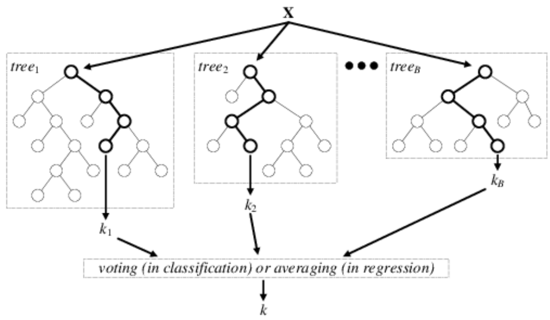

Figure 2: A simplified explanation of the random forest algorithm. X is the variable input, and k is the end result (Verikas et al. 2016).

2.4 Quality assessment

After the classification has been done, a quality assessment will be done. This includes stating the accuracy and the reliability. The accuracy is the number of objects correctly classified in a class as a percentage of the total number of objects actually belonging to that class in the image. The reliability is the number of correctly classified objects to the total number of objects assigned to a class (Coumou 2017).

The final classification will also be compared to some provincial statistics from the (General Statistics Office of Vietnam 2015) (GSOV). They provide information about overall statistics of several land usages, e.g. rice, forest, per province per year. However, these statistics lack explanation, therefore, it is unclear what exactly is counted to each class.

2.5 Data

Images of the Landsat 8 will be used. The Landsat 8 differs from TM 5, the TM has been replaced by OLI and TIRS. It has new spectral bands and some band widths have been adjusted. The data quality (signal to noise ratio) of the OLI and TIRS is higher than previous Landsat instruments, providing significant improvement in the ability to detect changes on the Earth's surface, as stated on the website of USGS. The images are taken in the period from January to March, preferably in February, since this is the dry period. The dry period should be the least cloudy. The images have less than 20 percent cloud cover.

The image that was chosen is:
Landsat 8, tile: WRS path 125, row 053, 24 January 2015, GeoTIFF.

This image was chosen since it had the least amount of cloud cover compared to other years, taken in the time period from 2013 to 2018.

The validation set of the General Statistics Office of Vietnam can be downloaded on their website. The data is displayed in table format and consist of data from 2015. Specific categories are available, but only rice and forest data were used.

3 Results

3.1 Classification accuracy

The final map can be observed in figure 3. The overall accuracy of the out-of-bag segments is 81.2% and the overall accuracy of the validation set is 83.6%, as can be seen in figure 4 and figure 5. The overall reliability and accuracies vary in land use classes and also vary between the out-of-bag set and the validation set.

The classes that preformed well in both sets were marshland / wasteland, with an accuracy of 100% and 94% respectively, triple crop rice / double crop irrigated rice, with accuracy of 98% and 93% and linear features with an accuracy of 89% and 100%. The classes which preformed relatively poor in both sets are mangroves, with accuracy of 60% and 57% respectively, urban open, with accuracy of 68% and 82% and industrial with accuracy of 78% and 50% respectively.

3.2 Comparison of provincial statistics

The classes which are compared to the provincial statistics are the rice classes and the forest classes. The ground truth data (General Statistics Office of Vietnam 2015) can be seen in figure 6. Spring paddy could correspond to triple rice / double cropped irrigated rice. Winter paddy could correspond to bare field - rain fed rice. Natural forest could correspond to mangroves and planted forest could correspond to plantations, see figure 6a and figure 6b. When comparing these classes, a difference is observed. The random forest classification delivered lower values in both rice classes and in forest classes compared to the GSOV data. In general, the forest classification is more accurate than the rice classification. The forest classification is in range of the same values as the GSOV data, but the rice classification is off in orders of one thousand, in some cases.

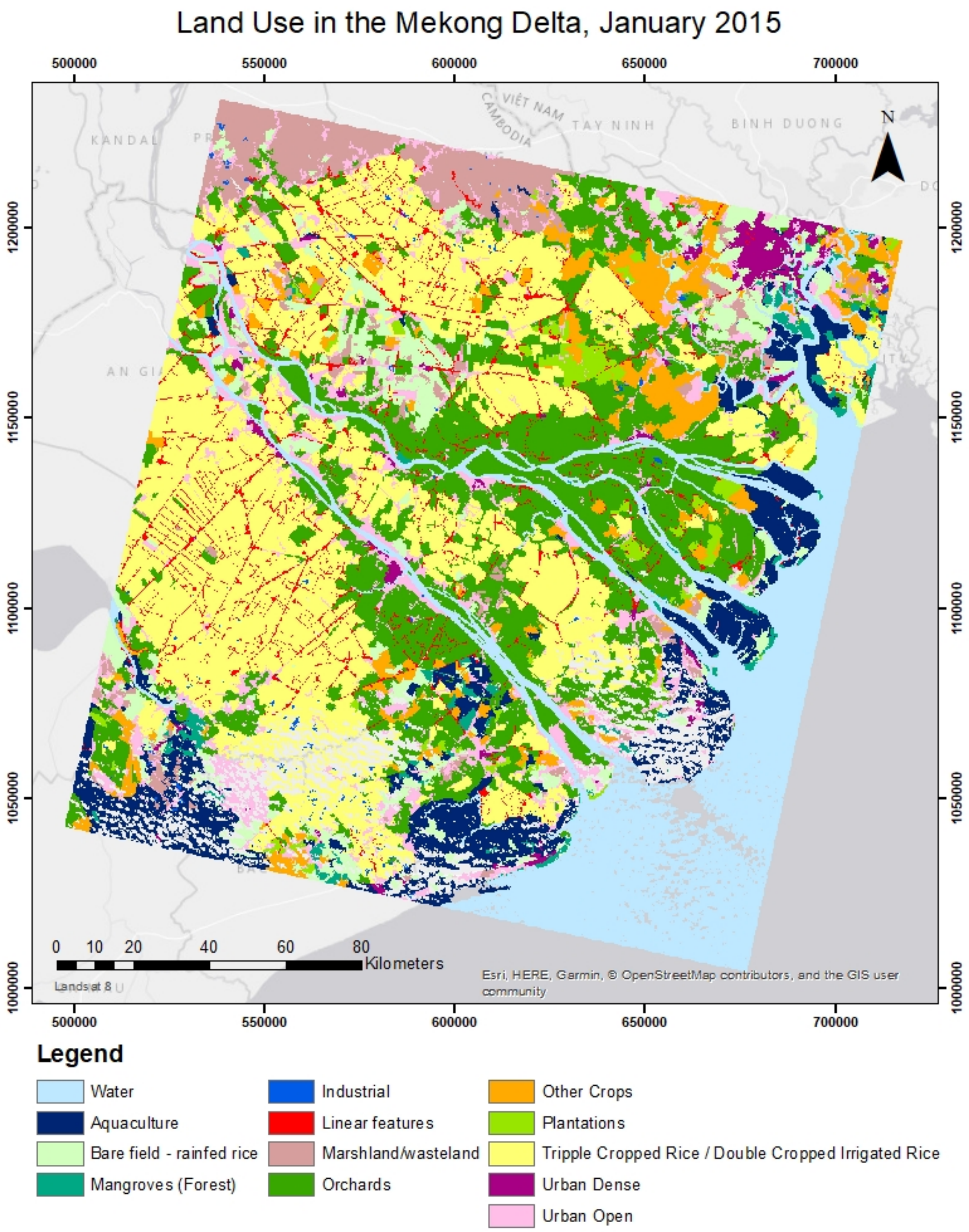

Figure 3: The land use classification of the Mekong Delta in January 2015. The parts with the same colour as the background (light grey), are no data polygons. These no data polygons are clouds.

Figure 4: The error obtained by using the ***out-of bag segments*** *of the random forest classification. The numbers indicate the number of segments that have the same class in the 'ground truth' validation set as in the classification (green) or the number of deviating segments (orange). Overall accuracy is provided in lower right corner.*

Reference Land Use Class

Predicted Land Use Class	Aquaculture	Bare field- rain fed rice	Mangroves	Industrial	Linear Features	Marshland / Wasteland	Orchards	Other Crops	Plantations	Triple Rice/Double irrigated rice	Urban Dense	Urban Open	Total	Reliability
Aquaculture	20	3	0	0	0	0	0	0	0	0	1	0	24	83%
Bare field – rain fed rice	0	26	0	0	0	0	0	0	0	0	0	1	27	96%
Mangroves	2	0	3	0	0	0	0	0	2	0	0	0	7	43%
Industrial	0	0	0	7	0	0	0	0	0	0	2	2	11	64%
Linear Features	1	0	0	0	17	0	0	0	0	1	0	2	21	81%
Marshland / Wasteland	1	1	0	0	0	33	0	1	0	0	0	0	36	92%
Orchards	0	0	2	0	0	0	35	2	0	0	0	0	39	90%
Other Crops	0	0	0	0	0	0	4	11	2	0	0	0	17	65%
Plantations	0	0	0	0	0	0	1	0	18	0	0	0	19	95%
Triple Rice / Double irrigated rice	0	0	0	0	0	0	1	0	0	40	0	0	41	98%
Urban Dense	0	1	0	2	0	0	0	0	0	0	17	3	23	74%
Urban Open	0	1	0	0	2	0	0	0	0	0	4	17	24	71%
Total	24	32	5	9	19	33	41	14	22	41	24	25	289	
Accuracy	83%	81%	60%	78%	89%	100%	85%	79%	82%	98%	71%	68%		81.2%

Figure 5: The error obtained by using the ***separate validation set*** *of the random forest classification. The numbers indicate the number of segments that have the same class in the 'ground truth' validation set as in the classification (green) or the number of deviating segments (orange). Overall accuracy is provided in lower right corner.*

Reference Land Use Class

Predicted Land Use Class	Aquaculture	Bare field- rain fed rice	Mangroves	Industrial	Linear Features	Marshland / Wasteland	Orchards	Other Crops	Plantations	Triple Rice/Double irrigated rice	Urban Dense	Urban Open	Total	Reliability
Aquaculture	17	2	0	0	0	1	0	0	0	0	0	0	20	85%
Bare field – rain fed rice	0	14	0	0	0	0	0	0	0	0	0	0	14	100%
Mangroves	0	0	4	0	0	0	0	0	0	0	0	0	4	100%
Industrial	0	0	0	1	0	0	0	0	0	0	0	0	1	100%
Linear Features	0	0	0	0	9	0	0	0	0	0	1	0	10	90%
Marshland / Wasteland	0	0	0	0	0	16	0	0	0	0	0	0	16	100%
Orchards	0	0	0	0	0	0	11	1	0	1	0	0	13	85%
Other Crops	0	0	0	0	0	0	1	3	2	0	0	0	6	50%
Plantations	0	0	3	0	0	0	0	3	7	0	0	0	13	54%
Triple Rice / Double irrigated rice	0	0	0	1	0	0	0	0	0	14	0	0	15	93%
Urban Dense	0	0	0	0	0	0	0	0	0	0	5	2	7	71%
Urban Open	0	2	0	0	0	0	1	0	0	0	0	9	12	75%
Total	17	18	7	2	9	17	13	7	9	15	6	11	131	
Accuracy	100%	78%	57%	50%	100%	94%	85%	43%	78%	93%	83%	82%		83.6%

Figure 6: (a) The total area in km^2 of rice and forest per province in 2015 provided by the General Statistics Office of Vietnam. Total paddies is not winter and spring paddy combined, but also takes autumn paddy into account, not presented here. Total forest is natural and planted forest combined. The blank spots are no data. (b) The total area in km^2 per province provided by the random forest algorithm

	Ben Tre	Can Tho	Dong Thap	Hau Giang	Long Ahn	Soc Trang	Tien Giang	Tra Vihn	Vihn Long	Total these provinces	Total Mekong Delta
Spring Paddy	172		2049	800	2339	1967	751	689	610	9377	16175
Winter Paddy	279	873			51	136		26		1365	2399
Total Paddies	630	2379	5460	2071	5229	3627	2247	2358	1805	25806	43015
Natural Forest	10				10	20		30		70	640
Planted Forest	31		522	26	247	85	39	57		1007	2081
Total Forest	41		522	26	256	105	39	87		1076	2720

(a)

	Ben Tre	Can Tho	Dong Thap	Hau Giang	Long Ahn	Soc Trang	Tien Giang	Tra Vihn	Vihn Long	Total these provinces	Total Mekong Delta
Triple Rice / Double cropped irrigated rice	33	899	1056	766	1741	559	605	460	582	6701	9432
Bare field – rain fed rice	101	0	547	57	223	183	15	28	24	1177	1903
Total rice	134	899	1603	823	1964	742	620	488	606	7879	11335
Mangroves	42	1	21	4	21	83	2	21	1	196	417
Plantations	121	0	28	4	57	38	140	11	0	399	469
Total Forest	163	1	49	9	78	121	142	32	1	595	886

(b)

4 Discussion

4.1 Classification problems

The object based approach of (Minderhoud et al. 2018) could be applied to Landsat 8 data, however it requires a sightly different approach compared to Landsat 5. It is unknown how the Landsat 5 data of Minderhoud et al. (ibid.) has been obtained. This could cause for differences in results, since GEE provides data in scale ratios, but other sources might not. This led to working with other parameters compared to the parameters which were used by Coumou (2017), which could possibly have influenced the differences in shape and size of the objects. This could be one explanation why objects were relatively big compared to (ibid.).

Since training areas had been selected manually, it has been difficult to distinguish certain classes. The objects generated where relatively big compared to the objects of (ibid.), in some cases, an object consisted of more then one class. The objects which consisted of more than one class were not chosen as training areas, but when they are classified by the algorithm, one class gets chosen and possible other classes also are classified to that class. This could explain part of the error. Some classes were hard to distinguish from each other. For example, the class 'other crops' was hard to distinguish from other vegetated classes. The spectral signature of 'other crops' is fairly the same as the spectral signature of other vegetated classes, such as plantations and rice.

The clouds caused for distortion in some cases, for example in the Southwest of the study area. In the Southwest, parts of the study area are classified as 'urban open', but when compared to the satellite image, they do not show the same spatial and spectral properties as urban open. This causes a higher area of urban open than expected. The area South of Ho Chi Mihn city also seems incorrectly classified. When looking at the area with Google Earth, this area is covered by small streets, with small houses which have small agricultural plots. It is hard to put the characteristics of this area in a separate class. Bare fields - rain fed rice and urban open cloud be a correct class for this area, but the parts classified as marshland would not be correct. There is no correct class for this part, so any agricultural or urban open will do. More research is needed on this area and how to classify this part.

The comparison to the data of the General Statistics Office of Vietnam is poor. This could be because it is unknown what the exact definition of the categories is. There is also no data of where these land usages are located. This makes it harder to compare. It could also be that the classification acted poorly or that the training sites were poorly chosen. However, since the exact definition and the exact location of these land usages is unknown, the validation of the GSOV data is not as important as the OOB accuracy and the validation accuracy.

4.2 Comparison to data of Minderhoud et al, (2018)

Since overall accuracy is above 80%, it overall is a good classification. However, it will be hard to compare the classified image with the data from Minderhoud et al. (2018). Firstly, the objects differ in size. Therefore, the land use changes which would occur will not be accurate since it is not on the same scale. Secondly, there could be interpretation differences. Since the training areas are chosen manually in this study and also were chosen manually in the study of Coumou (2017), it is impossible to tell if exactly the same features were chosen. Therefore, this data set cannot be used to compare to the Minderhoud et al. (2018) data. Finally, the data from Coumou (2017) compares relatively well to the data of the General Statistics Office of Vietnam, which can be seen in the appendix figure 9. The results of this study do not compare well to the GSOV data. This makes the results of this study questionable, however, (ibid.) only looks at aquaculture and dry season rice in 2006, while this study looks at different types of rice and different types of forest. No assumptions can be made regarding the importance of the data of the General Statistics Office of Vietnam.

5 Conclusions

The object based approach of (Minderhoud et al. 2018) can be applied to Landsat 8 data, but it requires a slightly different technique. The random forest algorithm performed well. The out-of-bag set accuracy is 81.2% and the separate validation set accuracy is 83.6%. However, the results do not compare well to the data from the General Statistics Office of Vietnam. The data cannot be used to compare to the data of (ibid.). This is because there is difference in object size and there could be differences in interpretation of land use classes between the two studies. In order to make assumptions about the land use change in the Mekong, at least two images need to be classified by the same person.

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Appendices

A Additional Figures

Figure 7: The percentages of land usage in the study area of the Mekong Delta.

	Percentage of total classified image
Aquaculture	8.1%
Bare field – rain fed rice	6.6%
Mangroves	1.4%
Industrial	0.3%
Linear Features	3.6%
Marshland/Waste land	5.7%
Orchards	24.3%
Other Crops	5.6%
Plantations	1.6%
Triple Rice / Double cropped irrigated rice	32.5%
Urban Dense	1.7%
Urban Open	8.6%
Total	**100%**

Figure 8: The area in km^2 of the different land use classes in several provinces. Only provinces which are fully in the stud area are taken.

	Ben Tre	Can Tho	Dong Thap	Hau Giang	Long Ahn	Soc Trang	Tien Giang	Tra Vihn	Vihn Long	**Total these province s**	**Total Mekong**
Aquaculture	433	0	13	7	116	610	85	249	1	1514	2334
Bare field – rain fed rice	101	0	547	57	223	183	15	28	24	1177	1903
Mangroves	42	1	21	4	21	83	2	21	1	196	417
Industrial	3	2	6	9	16	12	4	3	0	54	89
Linear Features	54	105	173	71	214	45	78	21	40	799	1046
Marshland/Waste land	9	0	132	1	72	34	0	41	26	316	1666
Orchards	1083	280	661	407	942	727	1086	499	615	6299	7046
Other Crops	106	0	98	60	517	100	169	45	19	1115	1621
Plantations	121	0	28	4	57	38	140	11	0	399	469
Triple Rice / Double cropped irrigated rice	33	899	1056	766	1741	559	605	460	582	6701	9432
Urban Dense	5	30	23	1	34	22	15	21	5	157	482
Urban Open	62	83	414	84	394	290	70	181	132	1710	2482

*Figure 9: The results of the study of Coumou (2017) compared to the data of the General Statistics Office of Vietnam in area in km^2. Dry-season rice (incl. harvested and partly dry-season rice class) is compared with the GSO category 'spring paddy. * GSO statistics represent the entire province, but RF does not when of the province falls outside the study area*

		Aquaculture						Forest		Dry-season rice					
		1996		2006		2009		2009		1996		2006		2009	
		RF	GSO	RF	GSO	RF	GSO	RF	GSO	RF	GSO	RF	GSO	RF	GSO
Coastal provinces	Ben Tre	341	247	467	410	480	420	40	38	221	218	359	207	331	211
	Tra Vinh	251	250	456	413	397	340	18	72	346	391	468	528	359	561
	Soc Trang*	152	241	293	643	541	692	82	105	385	614	737	1397	1031	1386
	Long An*	107	25	140	116	165	90	352	465	1325	1816	1511	2345	998	2490
Inland provinces	Hau Giang	-	-	0	74	1	62	29	25	-	-	783	842	852	823
	Tien Giang	30	92	59	124	75	126	144	88	798	877	872	839	829	827
	Vinh Long	2	11	4	23	7	25	3	-	709	738	481	697	720	676
	Can Tho*	0	105	5	136	3	131	4	-	1429	1636	769	930	606	901
	Dong Thap*	1	12	5	45	14	50	36	84	1788	1893	1723	2056	1331	2072

B Manual

B.1 Finding Data

As (Minderhoud et al. 2018) state, they use images of the dry season, from January to March. There are two ways to get the data. One way could be from the United States Geological Service, earthexplorer. This was my first approach. The user can set several parameters such as the data and the amount of cloud cover. I used Surface Reflectance values since these values are already pre-processed. I searched for images with less than 20 percent cloud cover and manually chose the best one. The images will be pre-processed after you have chose them by the USGS, this takes several hours to one day. Afterwards, they are ready to use.

My second approach was using Google Earth Engine, using this script:
https://code.earthengine.google.com/5fdd25e7e5d9fc4aa91031c1c4d672c2.
In this code; the clouds are already masked. However, this resulted in a small problem since GEE fills in NoData values with 1.#R, which could not be used in eCognition. For this, I clipped the image in ArcMap which fills in the NoData values with negative numbers. These negative numbers could be used in eCognition. This is however, a very insufficient approach and probably could be done more sufficient. Another problem which occurred with exporting data in GEE was that the pixel values were given in scale ratios, which results in very small values. This needed to be corrected in eCognition.

B.2 Object based analysis

There was chosen for a object based analysis. This is because the spectral values of the chosen classes are very similar. Some of the classes, such as aquaculture and bare field, also consist of several spectral values, which in a pixel based approach would be classified as other classes. The main advantage of eCognition over other software is the ability to assign classes based on properties of objects. These properties could be layers and indices but also object based characteristics such as length, width and so on.

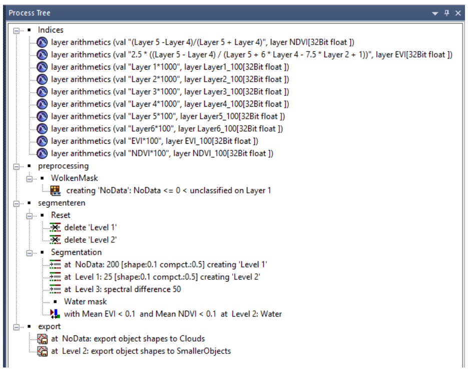

Figure 10: The ruleset used in eCognition. The children below the layer pre-processing node is specifically made for images from Google Earth Engine, since data is exported as scale ratios. Another image would not need this type of pre-processing.

In eCognition, the user makes a certain rule set, which describes the processes which have taken place. The rule set consists of nodes and children. The node typically is a description of processes which will occur as the children. The rule set I used is seen in figure 10 The most important parts for this rule set are the indices and the segmentation itself. The pixel values in the layers had to be edited since it did not work completely in eCognition. This is done with multiplying the layers with 1000 or 100, depending on pixel values. I decided to give the set the shape parameter to 25, since it generated smaller objects than the 200 which was mentioned in (Coumou 2017). After the objects had been generated, I manually chose my training areas. The were chosen based on comparison with the land use maps of Coumou (ibid.) and by visually looking at the NDVI, EVI, SWIR1, SWIR2, R-G-B and NIR-R-G. Afterwards, this manual set was exported as text file and as a shapefile. The shapefile was used in ArcMap to assign specific classes to. The clouds and water have been removed. A new column was added and for every classified training sample, a number was picked and added in this column. The was later exported as a text file with 28 properties to use for the random forest algorithm, while (ibid.) used 55 properties. The properties are shown in figure I did not know what the exact settings of several properties were, so I did not take them into account.

Layer values	*Mean*	Blue
		Green
		Red
		NIR
		SWIR1
		SWIR2
		TIR
		EVI
		NDVI
	Mode	Blue
		Green
		Red
		EVI
	Standard deviation	NIR
		SWIR1
		EVI
	Quantile	50^{th} EVI quantile
		5^{th} NDVI quantile
	Pixel-based	Max. red pixel value
		Max. SWIR1 pixel value
	To neighbors	Mean difference to neighbors: NDVI
		Mean difference to darker neighbors: NDVI
		Mean difference to darker neighbors: red
		Mean difference to brighter neighbors: EVI
		Mean difference to brighter neighbors: NDVI
Geometry	*Extent*	Area (pixels)
		Border length (pixels)
		Length (pixels)
		Length/width (pixels)
		Width (pixels)
	Shape	Asymmetry
		Border index
		Compactness
		Density
		Elliptic fit
		Radius of largest enclosed ellipse
		Radius of smallest enclosing ellipse
		Rectangular fit
		Roundness
		Shape index
	Based on skeletons	Curvature/length (only main line)
		Length of main line (no cycles) (pixels)
		Length/width (only main line)
		Maximum branch length (pixels)
		Standard deviation curvature (only main line)
		Width (only main line) (pixels)
Position	*Distance to vectors*	Distance to Ocean (outline) (pixels)
		Distance to Rivers (centroid) (pixels)
Thematic attributes	*Minimum overlap (%) with thematic polygons*	Ocean
		Rivers
Customized		(2*width+2*length)/border length
		Area/border length
		Mean difference to neighbors: 5% quantile of NDVI
		Mean of neighboring mean NDVI
		Standard deviation EVI divided by mean EVI

Figure 11: The properties which were exported with the generated segments. The one which were used for this study are highlighted in yellow. (Coumou 2017) used all properties.

B.3 Random Forest

A script was already prepared by (Coumou 2017). This script was mainly used as a reference, but I decided to make my own script, which is probably the easiest. I learned the most from the random forest session given by the VU and from this video.

For the classification, make sure that at least 5% of all objects is part of your training set. However, the more training areas, the better. Try to split your data set in 2/3 and 1/3 and use the 2/3 to train the algorithm. When the model functions properly, run the model on the validation set. Then you are ready to run then model on all the generated objects. The end result is a text file, which can be opened in ArcMap and then joined to the original objects. Convert polygon to raster to end with a classified image.