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Preliminary Study on the use of Sentinel-2A Image for Mapping of Dry Marginal Agricultural Land

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Abstract. The availability of medium resolution satellite imagery (i.e. Sentinel-2A) provides the rapid, low-cost and more accurate mapping. This report presents the use of satellite imagery (Sentinel-2A) for mapping of marginal Agricultural Land in the eastern part of Situbondo Regency. The study area covers three (3) districts, i.e., Arjasa, Jangkar, and Asembagus. This study uses two methods of image classifications (i.e., unsupervised and supervised). Sentinel-2A images for dry seasons of 2018 use for this study. The dry season of this region usually occurs from April to November. Then, 450 ground control point for training areas collected during the fields surveys between June until Octobre 2019. This study also uses multi-band (i.e., 2,3,4,5 and 8A) of the sentinel 2a image. Image treatments use “Multispect” and SNAP, two open-source image processing software. The procedures include image enhancement, registration, clipping, and classification. The classification consists of pre-processing, processing and post-processing tasks. Then, classification results evaluated by confusion-matrix (overall and kappa accuracy). Furthermore, the thematic maps produce from both unsupervised and supervised classification are then compared to existing thematics maps and statistics data. The unsupervised method use iso-data algorithm and produce five (5) class of land uses, i.e., (1) forestry and plantation; (2) build-up area, (3) irrigated paddy field, (4) non-irrigated rural areas (ladang/tegalan). The unsupervised method did the overall accuracy = 79 % and kappa accuracy = 72%. The supervised methods use maximum-likelihood algorithms and produce six (6) class, i.e., (1) forestry - plantation; (2) urban or build area, (3) irrigated paddy field, (4) non-irrigated rural areas, (5) dry-marginal land and (6) water body. Supervised method provide overall accuracy = 95,8% and kappa accuracy = 93,2%. The result shows the potential use of Sentinel 2A to map dry-marginal agricultural land in the study area.

Keywords: Sentinel-2A, Mapping, Dry-marginal, Agricultural Land, Supervised, Multi-band, Classification

1. Introduction

Situbondo regency located in the eastern part of East Java region. This region is subject to the tropical climate and drier than others sub-areas. The annual rainfall range from 500 to 2000 mm a year which less than average annual rainfall received in East Java (1500 to 2500 mm/year). The rainfall received per month is also very limited. Usually, rainfall more than 100 mm/month occur from January to April. The dry season of this region range from 7 to 9 months a year.

The soil properties in this region are characterised by a thin soil layer on the top of the primary rock. The soil layer has shallow solum and usually less organic matter. In many cases, we can find the



presence of gravel mix with upper soil layers. This stony soil layer usually finds on the top of the terrain, having slight to the moderate slope (Figure 1).



Figure 1. (a) Example of dry marginal agricultural land at Jatisari village. The photo was taken from the field survey in June 2018

Figure 1. (b) Example of dry marginal agricultural land at Jatisari village. The photo was taken from the field survey on 23rd November 2019

Moreover, macropores present on the soil layer that accelerates the runoff to infiltrate and percolate more rapidly in beneath the soil layer. Therefore a few of intermittent rivers flow over on this region. The combination of the shallow soil layer in stepped terrain drainage, the present of macropores and intermittent rivers continuously recharge the groundwater resources. The groundwater source is the primary source of water available in this region. However, pumping the water from deep groundwater source is still expensive and inefficient practice for agricultural purposes. The similar areas also found in central and western areas of the Regency. This widely land resources availability categorised as Marginal Agricultural Land (MAL) or *Sub-optimal land (SOL)*. Marginal agricultural lands can be defined as 'lands having limitations which in aggregate are severe for sustained application of a given use and/or are sensitive to land degradation, as a result of inappropriate human intervention, and/or have lost already part or all of their productive capacity as a result of inappropriate human intervention and also include contaminated and potentially contaminated sites that form a potential risk to humans, water, ecosystems, or other receptors' [1], [2].

In this study, Dry-MAL defined as land having low natural fertility due to the intrinsic properties and forming environmental factors [3]. This Dry-MAL appears mostly in the three districts i.e Arjasa, Jangkar and Asembagus. These districts are located in the eastern part of Situbondo Regency. The productivity of MAL is usually below the standard land capability. Therefore, the sustainability of agricultural practices in this area constrained by the input cost of plant productivity.

Furthermore, the economic value of water resources and the agricultural product has also restricted the usability of the DryMAL. However, the duration of dry seasons presents in this area do the benefit for grain seed production and some commodities. Some farmers in this areas plant Manggo as their primary incomes. However, the plantation occupied only fewer areas of this marginal land. Majority of this land resources is still un-usable specifically at the peak of dry seasons. The potential use of this land resources for agricultural practice is still an obstacle. Many efforts have been initiated to increase productivity and to reduce the obstacle. One of the efforts is by introducing public-private-partnership in grain seed production system. The region is positively supporting grain seed production. The grace of the length of dry seasons present in these regions, the area can be set as grain seed production centre by functioning the existing marginal land. Optimisation of the productivity of this land resources will be done the impact to the society through the addition of margin income from seed production and therefore increase the income of the farmer participants. In the first step, mapping of this marginal land is urgently required.

Sentinel 2A is one of the high-resolution imagery available for free download. The data can be downloaded from the USGS website (<https://earthexplorer.usgs.gov/>) or using sentinel hub at

<https://www.sentinel-hub.com/explore/eobrowser>. This global coverage satellite remote sensing system provides imagery at the global level. Furthermore, the imagery provides appropriate spatial, spectral and temporal resolution for identification and mapping of dry marginal agricultural land in this study. The use of satellite imagery for mapping in the agricultural areas is widely known methods and have published by many researchers around the world. Some examples of the use of Sentinel-2A imagery for identification and mapping in agricultural-related issues found in the many studies ([4], [5], [13]–[15]). These studies show the potential applicability of sentinel 2A for mapping land use and land cover or phenomenon related to the agriculture field.

The image classification based on the pixel is a widely known method to recognise and to map objects based on their digital number (DN Value) contained in the pixel. Two types of classification methods are widely knowns, i.e., supervised and unsupervised [17]. Supervised classification explores any available algorithms. The critical thing to be considered is the type and number of training areas and selected band combination used. Un-supervised classification uses any clustering algorithms to classify the pixels based solely on their similarity in DN value[18]. The objectives of this study are: (1) to map and to classifier dry marginal agricultural land (Dry MAL); and (2) to compare the map produced by the two methods of classifications.

2. Metode

2.1 Study site

Research conducted from March to October 2019. The area of study covers three districts in the eastern part of Situbondo, i.e., Arjasa, Asembagus dan Jangkar (Fig.2). Total area for the three districts is about 461,69 km².

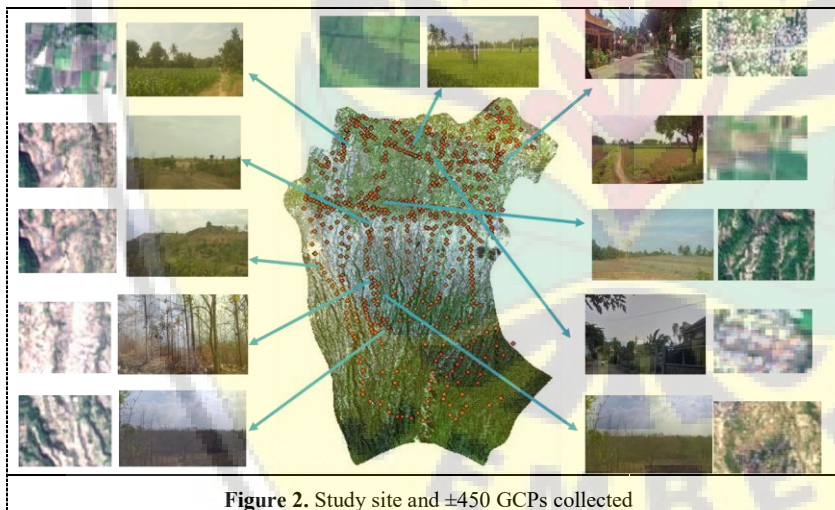


Figure 2. Study site and ±450 GCPs collected

2.2 Input Data

Primary input data for this study is the sentinel image of the location of interest. The image is selected based on minimum cloud cover present on the imagery. The image downloaded from the USGS web site (<https://earthexplorer.usgs.gov/>). Fig.2 and Table 1 visualised the raw image and metadata related to the image.



Others thematic maps used in this study downloaded from Indonesian Geospatial Agency (Badan Informasi Geospasial or BIG) through the web site (<https://tanahair.indonesia.go.id/portal-web>). The RBI (Rupa Bumi Indonesia) maps that downloaded from the BIG websites are used to compare the classification results.

2.3 Tool Used

In this study, a Multispec© software package version 9 [19] uses as the tool for image processing. Software downloaded from the website (<https://engineering.purdue.edu/~biehl/MultiSpec/>). Multispec© use to process image treatment that includes: image enhancement, pre-processing and classification. Another tool used in QGIS[20] an open-source GIS and Remote sensing software package. QGIS uses for atmospheric correction, re-classifier image and visualisation. Hardware used in this research is the Global Positioning System (GPS) and PC. GPS use to collect Ground control point (GCP) collection. Camera to capture the landscape at GCPs locations and PC use for processing data.

2.4 Procedure

The image treatment consists of atmospheric correction; image composite; field survey for collecting training areas; clipping; unsupervised classification; supervised classification; accuracy assessment; and image analysis & interpretation.

Dark Object Subtraction (DOS) algorithm uses to conduct atmospheric correction by using the Semi-Automatic Classification Plugin (SCP)[20] on the platform of QGIS.

We use five composites, bands of sentinel 2A (i.e., band 2,3,4,5 and 8A), both for unsupervised and supervised classification methods.

Several fields survey conducted between May to October 2019 to collect Ground Control Points (GCPs), to recognise the real condition in the field, and to take some photographs from the regions. About 450 GCPs are collected and used as training areas for supervised classification. Table 1 resumes the statistics of GCP samples used for each type of land use.

Table 1. Statistic of GCPs used for this study

Class Type	Number of samples	Total surface area (km ²)	Size of a sample (km ²)		
			Minimum	Maximum	Median
Pavement areas	83	35,171	0,016	0,521	0,053
DryMAL	75	121,04	0,015	0,563	0,056
Irrigated pady	87	114,41	0,016	0,636	0,511
Forest	58	163,94	0,013	0,370	0,032
Non-irrigated area	82	23,01	0,018	0,412	0,562
Water body	65	4,12	0,165	0,374	0,053

The image then clipped with a polygon that covers the three districts (Arjasa, Asembagus dan Jangkar) Boundary. Fig.2 shows the study area, collected GCPs, and photos taken during the field survey.

Unsupervised classification is done by using the iso-data algorithm and following the procedure as published on the tutorial [21],[22]. Firstly, the user sets the criteria of each cluster, then the ISodata algorithm calculates the distance for each pair of pixel and calculates the centre of the clusters. Furthermore, each pixel classified into clusters. Finally, the process is iterative until the targeted class.

In this study, the maximum likelihood algorithm uses to perform *supervised classification*. The classification explores the five composites bands of sentinel 2A (i.e., band 2,3,4,5 and 8A) and 450 GCPs as training areas. Classification procedure following the existing tutorial [22], [23].

Accuracy Assessments. We use the general concept of Overall and Kappa accuracy to evaluate the classification results and follow the existing tutorial to calculate the index [21]–[23].

Image interpretation. The map results from the supervised and unsupervised classification then compared with existing RBI digital maps downloaded from the BIG website.

3. Results and Discussion

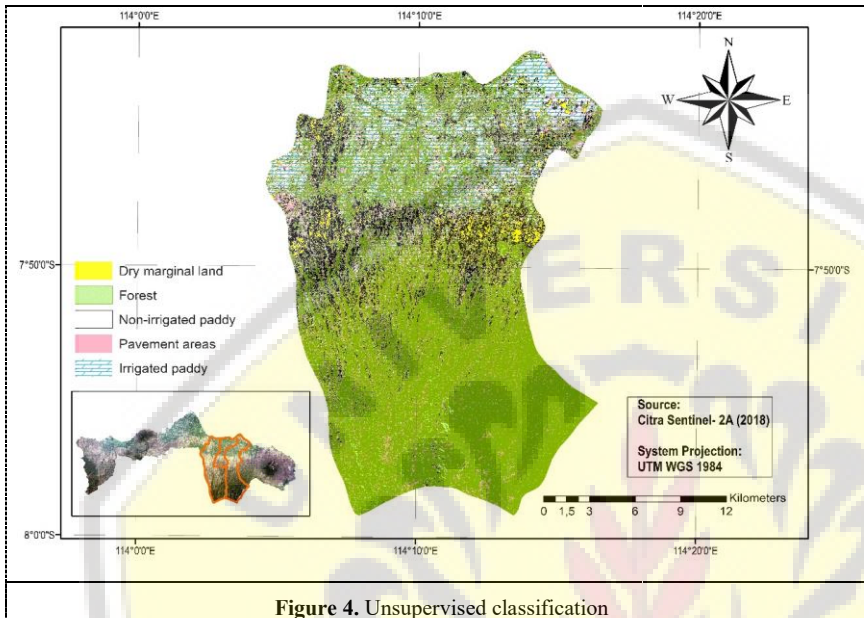
3.1 Unsupervised classification

Table 2 shows the confusion matrix result of unsupervised classification. This unsupervised method did the overall accuracy = 79% and the kappa accuracy = 72 %.

Table 2. Confusion matrix of unsupervised classification

Class	DryMAL	forest	Non-irrigated	Pavement	Irrigated	Total
DryMAL	119	10	5	0	28	162
forest	5	113	13	10	5	146
Non-irrigated	0	0	52	0	0	52
pavement	0	5	0	29	0	34
Irrigated	21	0	0	0	86	107
Total	145	128	70	39	119	501

Five classes identified by using the unsupervised method (Fig.4). The area of pavement occupied = 21% of the total area mapped. Then, dry-marginal land (DryMAL) occupied = 2,4%, irrigated paddy = 21%, non-irrigated (ladang) = 7,6%, and forest = 48%. This method has done overestimate of forest area, and underestimate of DryMAL, pavement area, irrigated and non-irrigated paddy. Fig.4 visualised the map produced by unsupervised classification.



3.2 Supervised classification

Figure 5 shows the result of supervised classification by using the maximum likelihood algorithm. The classification done the overall accuracy = 95,8% and kappa accuracy = 93,2%. The confusion matrix presented in Table 3.

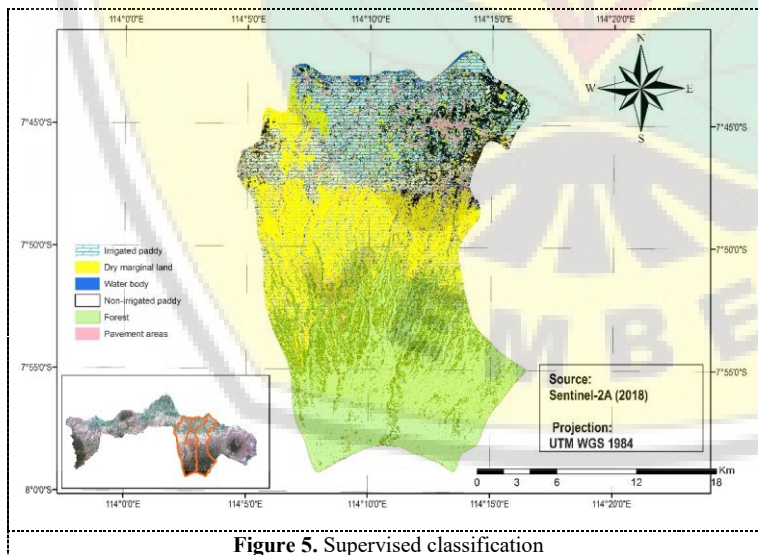


Table 3. Confusion matrix of supervised classification

Class Type	Irrigated	Dryland	Waterbody	Non-irrigated	forest	pavement	Total
Irrigated	13521	476	5	149	72	252	14475
Dry land	500	25270	38	118	34	218	26178
Water body	7	3	1802	6	0	56	1874
Non-irrigated	441	133	3	7017	1	66	7661
Forest	1608	354	4	9	67668	251	69894
pavement	111	129	33	62	0	2258	2593
Total	16188	26365	1885	7361	67775	3101	122675

Supervised classification can identifier and separated of Six (6) land uses occupations i.e.: irrigated paddy (24,78%), DryMAL(26,22%), Waterbody (0,89%), non-irrigated area (4,98%), forest (35,51%), and pavement or build-up area (7,62%). This supervised classification can distinct DryMAL and water body better than unsupervised methods. The classification results are zoned in a better way and more realistic compared to the reality in the field. In the upland area composed of forest and plantation which confirm the existing reality. The DryMAL, as investigated in this study, appear mostly in the middle area. Moreover, part of DryMAL also identified on the bottom-left of the study areas, and conform to the reality on the terrain.

3.3 Existing RBI Digital Map

Fig. 5 shows the Digital Maps available at Indonesian Geospatial Agency or Badan Informasi Geospasial (BIG) official site (i.e. <https://tanahair.indonesia.go.id/portal-web>). This map called as “RBI (Rupa Bumi Indonesia) format shp” in vector layer format and can be downloaded free of charge. The map for this area dated from the year 2000 to 2003. This official digital map is used to compare the two classification results.

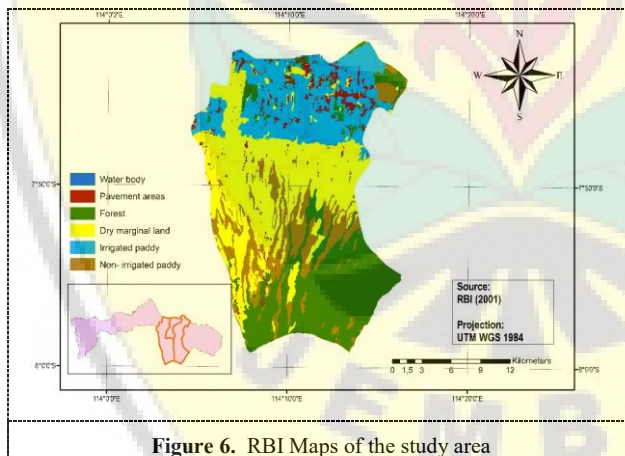


Figure 6. RBI Maps of the study area

According to this map, the total area for the three districts is 461,69 km². Land use occupied by: Dry-MAL (Ladang = 34,3%); Irrigated paddy field (22,0%); non-irrigated area (13,8%), Pavement or built-up area (3,5%); Forests and plantation (26,30%) and water body (0,10%).

3.4 Comparison of Maps

Table 4 present the class type in the coverage area (km²) and (%) of the total area mapped using unsupervised, supervised and RBI digital maps. It noted that the RBI map produced during the year between 2001 to 2003 and it is the official maps available at free of cost for most rural areas in

Indonesia. While for unsupervised and supervised classification derived from sentinel 2A imagery dated in the year 2018.

Table 4. Maps results

No	Land use Classe	Unsupervised		Supervised		RBI (2001 -2003)	
		(km ²)	(%)	(km ²)	(%)	(km ²)	(%)
1	Pavement area	94,56	20,48	35,171	7,62	16	3,5
2	Dry-marginal land	10,86	2,4	121,04	26,22	158,4	34,3
3	Irrigated paddy	97,9	21,21	114,41	24,78	101,4	22,0
4	Forest and plantation	223,4	48,38	163,939	35,51	121,4	26,30
5	Non-irrigated area	35,0	7,58	23,011	4,98	63,9	13,80
6	Waterbody			4,12	0,89	0,60	0,10
	Total	461,69	100,00	461,69	100,00	461,7	100

The supervised classification produces the result better than un-supervised classifications and can be used to update existing information on the RBI Digital Maps. In the RBI map (table 4), the pavement area covers only 3.5% of the total area mapped, and therefore from the year 2001 to the year 2018, this pavement area may increase until 7.62% of the total area mapped. It is due to the population increase and the development in the villages. The unsupervised method overestimates the pavement area.

Supervised classification algorithm can help identify water body better than un-supervised. The waterbody area increase in the supervised map by + 0,79% of total area, because of the development of aqua-cultures sites. The sites developed to breed the shrimp and to harvest salt and located along the coastal line of the region (the northern part of the map). Sentinel 2A band can identify this site better. It is shown that this type of industry supports part of economic development in the regions.

An irrigated paddy field is a relatively land use that consistently mapped both using supervised, unsupervised and the RBI. It is normal that in the region, the development of the irrigated area is relatively constant during the last twenty year. The primary canal for irrigation passed over the maps and divided the region significantly into two distinct land use occupation. Referring to Fig.4 (on the RBI map), it shows that below the canal we can find the irrigated area (irrigated paddy with blue-light colour legend). This area covers about 22% of the total area on the map. The government build the canal in the period between 1980 to 1985. The region of interest is the driest area in East Java. The water flowing to this area and it comes from the Sampean Reservoir's that located ± 40 km from the region. This region is the last downstream areas covered by the canal, and therefore the water availability is minimal for irrigation. In the three maps above, we can show that irrigated paddy is calculated slightly different amongs 22% (in RBI map), 24,78% (in the supervised map) and 21,21% (in the unsupervised map). It noted that the region received more rainfall in 2018, and therefore more agricultural areas (both in irrigated and non-irrigated areas) are planted with existing crops. In the sentinel image classified by the supervised method, it appears as the addition of the irrigated area. The conversion from agricultural field to pavement areas has also appeared in the area below the canal. It noted that in parallel to the coastal area (in the northern part of the map) we could find the national route that links Sumatra, Java and Bali Islands.

The shift in the land occupation on the region can be observed using three classes of land uses these dry-marginal land (DryMAL), forest and plantation (Forest), and non-irrigated area. The original land resources of these three classes are actually similar, i.e. Marginal dry land on this region. Subtotal area occupied by these three classes in RBI map = (34,3 + 26,30 + 13,80) = 74,40% and on the supervised map, the subtotal areas = (26,22 + 35,51 + 4,98) = 66,71%. It shows the potential of dryland resources in this region. The efforts of the government and stakeholders to optimise this DryMAL resource achieved by comparing these three classes of land use. The DryMAL and non-irrigated area gradually shift to mango plantation. However, in the Sentinel image, it is still difficult to separate Mango and forest tree cover, because this appearance is similar to permanent vegetation.

4. Conclusions

This study shows the potential applicability of sentinel 2A imagery for the identification dan classification of Dry Marginal Agricultural Land (DryMAL) on the area of study. Sentinel 2A image dated in 2018 downloaded and used for DryMAL mapping. Supervised and unsupervised methods used to perform image classifications processes. In this case, Multispec© software package used as a primary tool for image classification. The use of unsupervised method produce five(5) main land-use class, i.e., Pavement area, DryMAL, irrigated paddy, non-irrigated area, and forest-plantation. The classification is done the overall and kappa accuracy = 79% and 72% respectively. The supervised method performs better classification and can distinguish six (6), land-uses classes, i.e., pavement area, DryMAL, irrigated paddy, non-irrigated area, forest-plantation, and water body. The supervised method performs the acceptable value of overall and kappa accuracy at 95,8% and 93,2%, respectively. The comparison of the detailed map with existing digital maps explains the shift and change in land use occupation. This positive change shows the prove of stakeholders efforts to increase the usability and productivity of DryMAL. Finally, the supervised classification performs the results better then un-supervised classifications and can be used to update existing information on the RBI Digital Maps.

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