Assessing the paddy fields conversion using optical satellite imageries: A case study in Karawang Regency, West Java

S. Suliman1, Y. Setiawan2, Syartinilia3

1Department of Natural Resources and Environmental Management, IPB University, Baranangsiang, Bogor 16144, Indonesia.
2Department of Forest Resources Conservation and Ecotourism, IPB University, Fem Building Dramaga, Bogor 16680, Indonesia.
3Department of Landscape Architecture, IPB University, Chemistry Building 2nd Floor, Dramaga, Bogor 16680, Indonesia.

E-mail: salim.mohemad@gmail.com

Abstract. Paddy fields are the most crucial agricultural land-use in Indonesia that supporting national food security. Such lands have been experienced a massive change in their dynamics, specifically in rice production home, West Java. Karawang paddy fields notably become the major victim of land-use change along with rapid economic growth, development, and population pressure. This study aimed to assess paddy fields’ conversion dynamic and how land-use change contributes to this issue in Karawang. Remote sensing techniques and satellite images were used for investigation across the Karawang Regency. Three kinds of satellite image datasets of Landsat 5 TM, Landsat 8 OLI, and Sentinel 2 during the periods of 2009, 2014, and 2019 were analyzed. The results revealed that land-use change impacted paddy fields conversion significantly. Karawang regency lost 16346.77 ha or 8.54 % of its paddy fields throughout the study period. Such farmlands declined by 8639.84 ha (4.51%) and 7706.93 ha (4.02%) between 2009 -2014 and 2014 to 2019, respectively. The conversion of paddy fields to build areas, including road infrastructures, is approximately 14536.21 ha, representing 57.98% of the total paddy fields converted. It concluded that paddy fields had faced massive conversion over the last ten years driven by conversion into buildup areas due to the increased land demand, i.e., residential, commercial, and industrial activities.

1. Introduction
Human alterations on Earth's surface are unprecedented today regarding space, magnitudes, and spatial extent. The most apparent indicator for such surficial alterations is a change of Land cover (biophysical properties of the Earth's surface) and land-use change (human intent or purpose applied to these features). However, the development of economic growth along with population pressures continues to increase significantly in developing countries. Due to that, demand for land as a production factor or consumption good also increasing simultaneously. As the land availability is limited, ongoing population pressure and economic development imply that land-use change is inevitable[1,2]. Land-use change is a process of
change in land function from a particular function to another function, e.g., farmlands to a residential area. Existence of numerous advantageous factors such as strategic location and availability of infrastructure[3], i.e., existing road network and irrigation [4], prime farmlands become the typical victim of land-use change.

In Indonesia, 26 out of 33 provinces are characterized by the existence of paddy fields. Such farmlands, especially the wet paddy farms, are not merely producing rice. Yet, they also support fish cultivation(agro-fisheries), minimizing soil erosion, controlling floods, recharging groundwater, regulating ecosystem services, and maintaining biodiversity’s [5]. Despite the importance of such farmlands and their indispensable contribution to the national food security and food self-sufficiency, land-use change is converting tremendous farmlands areas, particularly on Java Island. Java has the highest population density, where the land is needed to meet the rapid growth of physical development. The island has nearly 50% of total paddy fields, while 30% exists in West Java Province[6].

Karawang Regency is the top rice-producing regency in west java province. Despite the regency area representing 4.6% of the province area, it has nearly 12% of the paddy fields of West Java, and approximately 15% of West Java rice production emanates from it [7]. The regency experienced massive land-use change over the land for three decades. Its lost 18460.8 ha of its paddy farmlands between 1994 – 2015 [8]. The regency paddy farmlands had been reduced from 120,371 ha in 2000 to 98.462 ha in 2015, and it's projected to be just 95.556 ha in 2031 [9][10]. The history of land-use change began in the 1980s when Indonesia intended to encourage investors and open avenues for investments. Due to that, extensive land occupancy in general and farmlands with a strategic location, particularly in the peripheral area, have been victimized by land conversion. Hence the massive change of farmlands will diminish the potential food security and food self-sufficiency in the near future. Therefore, the availability of accurate, current, and long-term Information on paddy farmlands and the annul conversion rate will be vital in designing appropriate governmental policies [11].

Advances in computing power and the increasing availability of Remote Sensing (RS) data have renewed interest in using Geographical Information Systems (GIS) to address a wide range of environmental issues. This includes utilizing medium/high-resolution satellite imagery provided by free open datasets, i.e., Landsat and Sentinel. Such data are used in the spatiotemporal analysis of landslides prediction, drought monitoring, climate change observations, quantifying land use and land cover changes (LULCC), and identifying each class's annual rate of change. LULCC can be quantified by processing and classifying satellite images based on spectral signature using traditional GIS software or cloud computing platforms. Supervised or unsupervised image classification using traditional software such as ERDAS IMAGE, QGIS, and ArcGIS, characterized by two main challenges; big data needs to be processed, requiring more extensive storage. And the availability of images cloud-free over the study area. The process consists of searching, filtering, downloading, layer stacking, and mosaicking. Big data, not just time-consuming but also needs high power computing and significant storage capacity. Besides that, it is not so easy to obtain an image without or with a low cloud cover percentage, especially within tropical regions.

On the other hand, the development of cloud-based computing platforms, e.g., Google Earth Engine (GEE), facilities to overcome most challenges of traditional methods. GEE addressed the most significant difficulties regarding land use and land cover mapping over large areas. GEE makes it easy to navigate, browse and analyze all available RS data sets images via a web-based Integrated Development Environment; code editor without downloading images to the personal computer. Besides fast in computing, another that makes it more preferable is the availability of a bunch of algorithms to simplify access and perform both supervised and unsupervised classification. Algorithms of supervised classifiers include; American Museum of Natural History Maximum Entropy (amnhMaxent), decision Tree, decision Tree Ensemble, Classification and Regression Trees (smileCart), smileRandom Forest (RF), plus other algorithms for performing accuracy assessment [12]. Consequently, this paper aimed to quantify paddy fields conversion (LULCC) in Karawang Regency between 2009-2019 using Tree Random Forest classifier.
2. Methodology

2.1. Study Area
The study was conducted in Karawang Regency, West Java Province. It's located between 107°02’ and 107°40'E, 5°56’ – 6°34'S in the northwest part of Java Island, Indonesia (Figure 1). It covers an area of 1,753.27 km², it is known as regional industrial activities and economic centers surrounded by cities such as Jakarta, Bogor, Depok, Tangerang Bekasi, and Bandung. The regency is populated by 2,44 million and consists of thirty sub-districts consist of 297 villages and 12 Special villages.

![Figure 1. Map of study Area](image)

Karawang was regionally divided into two major landscapes: lowland and coastal areas on the northern part with elevations ranging from 0 to 50 m and a hilly area on the southern part with elevation from 50 to 1,291 m above mean sea level. [8] stated that Up 95% of low land areas which classified as the S1 category (very suitable) for planting the paddy

2.2. Data Collection and Methods
The primary data were used in this study are optical satellite imageries, i.e., Landsat 5 TM (2009), Landsat 8 OLI (2014), and Sentinel-2 OEM (2019). Besides these data, such as administrative boundaries, shapefile was used. The land-use change technique in the study entails image pre-processing, normalization, the reference dataset, land use classification, and accuracy assessment. The technique was applied and evaluated by developing code in the GEE platform using a supervised classifier algorithm, i.e., Tree Random Forest. As shown in table 1, the median filtering was applied for Landsat and Sentinel-2 images for each chosen year. This is to remove/optimize the noise, minimize seasonality effects and avoid miss classification. High-resolution aerial imagery available in Google Earth and GEE base map was used as a reference layer to
obtain training data and validating the classifications. Comparisons were made between the classified images to find areas where the paddy field conversion takes place. The general procedures are summarized in the flowchart illustrated in Figure 2.

| Material/satellite image | Type | Resolution | Acquisition date | Source |
|--------------------------|------|------------|------------------|--------|
| Administration boundaries | Vector | - | Bappeda |
| Landsat 5 TM | Raster 30 m | June – August 2009 | USGS (https://www.usgs.gov) |
| Landsat 8 OLI | Raster 30 m | June – August 2014 | USGS (https://www.usgs.gov) |
| Sentinel-2 OEM | Raster 10 | June – August 2019 | European Union/ESA/Copernicus (https://sentinel.esa) |

2.3. Image Preprocessing

GEE is a platform that facilitates fast analysis by using the available google computing infrastructures. Pre-processed Landsat and Sentinel imagery available via GEE were utilized to assess paddy field conversion across the regency. GEE provides online access to hundreds of datasets, i.e., archived collection of Landsat data from USGS and Sentinel data from ESA collection (Table 1). The Pre-process of such data was conducted using cloud-computing techniques in the GEE. The median pixel values of imagery scenes of Landsat5, Landsat8, and Sentinel-2 were used for the years 2009, 2014, and 2019 respectively (Table 1 and Figure 2). To improve the reproducibility of the classification, an algorithm called Fmask (function of mask) was utilized to create precise observations of cloud and cloud-shadow-free images by selecting the best could-free pixel.

![Figure 2. Flow chart of input data, data processing, and generated LULC maps](image-url)
2.4. Land Use Categories and Reference Datasets

Using medium-resolution imagery to classify heterogeneous landscapes is a challenging task. Such heterogeneous landscapes of Karawang included 11 land use classes and three land cover classes based on the (SN176 451:2014) Indonesian National Standard. Yet, due to the difficulties in identifying some classes by a medium-resolution image of Landsat, they categorized all classes into seven land use classes based on this previous study [8]. The identified classes were 1) Forests, 2) Open Water Bodies, 3) Build-up Areas, 4) Fishponds, 5) Drylands/mixed gardens, 6) Bare lands, and 7) Paddy fields (Table 2). The reference datasets are an essential consideration in remotely sensed data for both training data and accuracy assessment. Up to 200 reference points, lines and polygon were delineated for each land-use class for each of these years 2009, 2014, and 2019 respectively. Such reference data are both from the based map of GEE and imported from Google Earth. The reference data consisted of 85% of randomly selected points, lines, and polygons as training data. The remaining 15% were used as the accuracy assessment dataset. The training data was used to improve the machine learning supervised classifier, whereas the accuracy assessment dataset was used to validate the land use classifications map.

Table 2. The adopted land use land cover classes base on the previous study conducted in the regency

| No | Land use/land cover          | Description                                                                                                                                                                                                 |
|----|------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1  | Fishponds                   | The entire area consists of ponds that function as fish or shrimp farming.                                                                                                                                     |
| 2  | Paddy fields                | The entire area that functions as a rice field area, both irrigated and rain-fed.                                                                                                                             |
| 3  | Dryland/Mixed gardens       | The entire populated area consists of various vegetations, both low and high, which are patterned and quite regular.                                                                                           |
|    |                              | Any significant clustering of tall (15-m or higher) dense vegetation, typically with a closed or dense canopy; examples include wooded vegetation and dense, tall vegetation clusters. It can also be a natural forest or managed forest. |
| 4  | Forests                     | Areas where water is present most of the year; may not include sporadic or ephemeral water; contains little to no sparse vegetation, no rock outcrops, and no built-up features such as docks; examples: rivers, ponds, and lakes. |
| 5  | Water bodies                | Human-made structures; major road and rail networks; large homogeneous impervious surfaces such as parking structures, office buildings, and commercial, industrial and residential housing; i.e., houses, dense villages/towns/cities, paved roads, and asphalt. |
| 6  | Build up areas              | The entire area is covered only by pioneer types of plants or entirely in the form of an empty expanse with rocks without plants.                                                                            |
| 7  | Bare lands                  |                                                                                                                                                                                                            |

Source [6]

2.5. Image Classification and Accuracy Assessment

Within the GEE environment, various classification algorithms can be utilized in mapping the LULCC using remotely sensed data [13]. The algorithms can be categorized as supervised and unsupervised classifiers. Supervised machine learning classifiers include; amnhMaxent, smileCart, RF, and Smile Gradient Tree Boost (GTB). These classifiers have been used intensively to classify optical satellite imageries. The RF and GTB classifiers effectively classify images compared to other classifiers; they even analyze data with intense noise[12]. For instance, a study aimed to generate a highly accurate agricultural activity map of dryland agronomy. It compared four different classification algorithms with the same training data. RF classifier performed the best result. Another study was successfully able to classify land cover using that same classifier algorithm [14]. An RF algorithm was employed in this study to classify and generate the desired land use classes for each chosen year. Such a classifier is an ensemble algorithm that uses bagging
techniques or "Bootstrap aggregating" to generate classification ensembles in a multiple decision tree manner. Each tree trains over a specific subset of the entire training data. In our study, ensembles of 30 trees were grown using the training data [15]. The developed model of RF classifier entails merely two parameters to be identified; the number of desired ensemble trees and, number of prediction variables used in each node to make the tree grow [16]. In satellite image classification, image validation is one the most important steps, where it's a valuable and effective way to assess how well the classification process achieved the study objectives. The developed land use classification map was validated using 20% of the reference dataset. Considering previous studies [17], a confusion matrix was constructed to assess the accuracy of classified maps using producer accuracy, user's accuracy, and Kappa statistics [18].

2.6 Change Detection Analysis
Change detection is the process of identifying differences in the state of a feature or land use/land cover class by observing it at different times [19]. Such analysis detects the differences between images of the same spatial extent but at different temporal intervals. The land use classified images were imported to ArcGIS to calculate the area of each class along with the images. The INTERSECT tool that exists Geoprocessing Bar was utilized to designate the differences in the area of each class. The generated data from the process of INTERSECT is exported from the attribute table of each image into Excel to perform further calculations. Figure 2 is a flow chart displaying how the analysis was performed to detect the changes between 2009 -2014, 2014- 2019, and 2009-2019 images.

3. Results and Discussions

3.1. Distribution of Land Use/Land Cover
Land use land cover maps were developed using RF supervised classifier for the years 2009, 2014, and 2019 in a total of Seven standard land use/land cover classes (Figure 3). The individual class area for the three years images is summarized in Table 4. The obtained overall accuracies were 97.48% (2009), 85.75 % (2014), and 92.85 (2019), respectively. The classification accuracies were produced by utilizing high-resolution imagery existing in the GEE-based map and Google Earth. The User and Produce accuracies of each class and Kappa coefficient are shown in (Table 3).

| No | Types                 | 2009 PA (%) | 2009 UA (%) | 2014 PA (%) | 2014 UA (%) | 2019 PA (%) | 2019 UA (%) |
|----|-----------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1  | Forests               | 90.00       | 100.00      | 70.00       | 70.00       | 70.00       | 100.00      |
| 2  | Water Bodies          | 90.00       | 75.00       | 80.00       | 80.00       | 100.00      | 100.00      |
| 3  | Build up Area         | 97.50       | 97.50       | 90.00       | 100.00      | 92.50       | 94.87       |
| 4  | Fishponds             | 93.33       | 96.55       | 93.33       | 100.00      | 93.33       | 93.33       |
| 5  | Dryland/ Mixed gardens| 100.00      | 95.24       | 80.00       | 88.89       | 90.00       | 94.74       |
| 6  | Bare lands            | 60.00       | 66.67       | 100.00      | 66.67       | 80.00       | 66.67       |
| 7  | Paddy fields          | 90.00       | 90.00       | 94.00       | 88.68       | 100.00      | 94.34       |
|    | Overall accuracy (%)  | 91.76       | 89.41       | 92.94       |             |             |             |
|    | Kappa statistics (%)  | 89.74       | 86.84       |             |             |             |             |
Over the whole study intervals, paddy fields dominated the area of regency. Its represented 64.14 %, 59.63%, and 55.60% of the Karawang area in 2009, 2014, and 2019 respectively. Such farmlands reduced by 8639.84 ha (4.51 %) in 2014 compared to 2009. It also reduced by 7706.93 ha (4.02%) in 2019 compared to 2014. While the buildup area is the second-largest land-use class occupied 11.13 %, 12.10%, and 18.14 % of the total regency area in 2009, 2014, and 2019 respectively. Based on Indonesian National Standard SNI 7645-1:2014, the land-use class of buildup area included sub-classes of residential, commercial, and industrial areas and road infrastructures and government buildings. It's evident that the urban areas and infrastructure expansion were continuously increasing over time. These subclasses increased by 13412.80 ha (7.00%) in 2019 compared to its area in 2009 (Figure 3 and Table 4).

Table 4. The distribution of land use and land cover classification for each year.

| No | Land use/land cover classes | The coverage area for each year |
|----|-----------------------------|--------------------------------|
|    | 2009 | 2014 | 2019 |
|    | ha   | (%)  | ha   | (%)  | ha   | (%)  |
| 1  | Forests       | 10907.73 | 5.70 | 16839.97 | 8.79 | 14314.04 | 7.47 |
| 2  | Water Bodies  | 3044.93  | 1.59 | 3234.35  | 1.69 | 3679.78  | 1.92 |
| 3  | Build up Areas| 21321.39 | 11.13| 23174.04 | 12.10| 34734.20 | 18.14|
| 4  | Fish ponds    | 16234.97 | 8.48 | 13850.07 | 7.23 | 15271.61 | 7.97 |
| 5  | Drylands      | 14978.14 | 7.82 | 14769.15 | 7.71 | 13557.33 | 7.08 |
| 6  | Bare lands    | 2199.94  | 1.15 | 5460.58  | 2.85 | 3477.72  | 1.82 |
| 7  | Paddy fields  | 122839.48| 64.14| 114199.64| 59.63| 106492.71| 55.60|
| 8  | Total         | 191526.58| 100.00| 191526.58| 100.00| 191526.58| 100.00|

The other land use classes, fishponds, and drylands/ Mixed gardens, all together represented 31213.11 ha (16.30%), 28619.22 ha (14.94 %), and 28828.94 ha (15.05%) in 2009, 2014, and 2019 respectively. These classes combined declined by 2593.89 ha (1.35 %) between 2009 and 2014. In comparison, they experienced substantial intensification between 2014 and 2019, increasing 209.71 ha (0.11%). On the other hand, land cover classes, forests, water bodies, and bare lands collectively showed a significant increase in the first study interval 2009-2014 (by 9382.30 ha or 4.90%). Their area decreased in the second study interval 2014-2019 (by 4063.35 ha or 2.12 %). At the same time, the areas of land cover increased by 5318.94 ha (2.78%) over the whole study period (2009-2014). This is due to the significant expansion of the barren land and forests areas (Figures 3 and 4).
3.2. Change Detection and Paddy Fields Conversion

Throughout the study period of 2009 – 2014, approximately 143932.72 ha or 75.15 % of the Karawang Regency area remained unchanged. In contrast, 47593.86 ha or 24.85% of the area has changed. During this study interval, the conversion of paddy fields to the other land use classes was estimated to be around 19511.91 ha, equivalent to 41.00 % of the total changed area (ha). The conversion from paddy fields into buildup areas dominated the land-use change of paddy farmlands. However, nearly 8275.47 ha of paddy field in 2009 converted into a built-up area in 2014, corresponding to 17.39% of the total changed area (Figures 4 and 5) and equivalent to 42.41 % of total converted paddy fields.

Conversely, approximately 143119.70 ha or 74.73% of the Regency area remained unchanged in the second study interval 2014 -2019. In contrast, 48406.88 ha or 25.27% of the area has changed drastically. Out of this changing area, 18473.55 ha or 38.16 % was paddy field converted into other land use classes. Equally, conversion from paddy fields to buildup areas remained conquered. However, buildup areas such as road infrastructure, residential, and commercial, replaced 10681.81 ha of paddy fields, representing 22.07 % of total change area and 57.82 % of total converted paddy farmlands (Figure 6). Suppose 10% of converted paddy fields are ignored for the sake of estimation accuracy. In that case, the annual paddy field conversion is approximately 1.83%/year of the Regency area in the first study interval and 1.74%/year over the second study interval.

![Figure 4. Converted and Unconverted paddy field maps 2009 -2019](image)

![Figure 5. conversion of paddy fields into other classes in period of 2009-2014 (a) and](image)

![Figure 6. conversion of paddy fields into other classes in period of 2014-2019](image)
These figures indicate that all adopted government measures assigned to control land-use changes/protect agricultural lands are not effective in controlling paddy field conversions throughout the study period. However, since 2009 Indonesian government has adopted law No 41 concerning the protection of sustainable agricultural lands. But the current conversion rate is closely aligned with [20], who estimate paddy fields conversion before 2009. It is being argued that the conversion of paddy fields is driven by its proximity to the nation's capital, where the land is highly demanded for commercial, industrial, and residential activities.

Based on the findings, urban expansion has caused the steady spreading of land use classes, especially paddy fields. Where the primary land-use change was a conversion of paddy fields into buildup areas due to rapid physical development around the urban areas, considering that the country's rice production is heavily centered on Java Island. Proximately 30% of production emanated from West Java Province. At the same time, Karawang is a rice production center in the province; the Paddy fields conversion rate of 1.83%/year implies that the rice production and national food security are at stake. In other words, giving the condition that; conversion of agricultural land into buildup area is irreversible[21,22], making new agricultural land will not obtain the same productivity in a short time, and land resources are becoming scarcer. Hence, the current trends of land-use change will negatively impact national food security [23].

4. Conclusion
The availability of the historical satellite's imageries from free-access datasets such as Landsat, Sentinel, and the new geospatial GEE technology represents a major improvement for monitoring land-use change with little effort and time consumption. This is a possible event over a large geographic region. This study successfully performed sub-province scale analysis and determined the distribution of land use land cover classes across the Karawang Regency, where the classified images obtained reliable accuracies. A total of 8275.47 ha of paddy fields in 2009 was replaced by buildup areas in 2014, and 10681.81 ha of paddy fields in 2014 converted into buildup areas in 2019 with an annual average conversion rate of 1.83 and 1.74%/year respectively.

It observed that land-use change was dominant in paddy fields throughout the all study period. As its focused-on paddy fields conversion, the study effectively quantified the spatiotemporal of paddy fields conversion over 2009-2019. It highlighted the share of buildup in the land-use change process.

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