# Comparison between top and bottom of atmosphere Sentinel-2 image for mangrove mapping in Balikpapan Bay, East Kalimantan

**D N B Ginting[1*], K T Setiawan[2], N Anggraini[2], A P Suardana[1], M R Nandika[1], A Ulfa[2], K Aziz[3], R Dewanti[2]**

[1]Research Center for Oceanography, National Research and Innovation Agency, Ancol, North Jakarta 14430, Indonesia

[2]Research Center for Remote Sensing, National Research and Innovation Agency, Cibinong, West Java 16915, Indonesia

[3]Center for Data and Information, National Research and Innovation Agency, Cibinong, West Java 16915, Indonesia

*E-mail: devica.natalia.brginting@gmail.com

**Abstract**. Sentinel-2 is high-resolution multispectral imagery that launched by the European Space Agency on June 23, 2015 for Sentinel-2A and March 7, 2017 for Sentinel-2B. The two satellites were launched with the aim of land monitoring studies, including vegetation, soil, and water cover, as well as the observation of inland waterways and coastal areas. In 2018, Sentinel-2 produced bottom-of-atmosphere (L2A) imagery derived from top-of-atmosphere (L1C), which has been atmospherically corrected using Sen2Cor algorithm. However, there is an overcorrection effect due to inaccuracies of digital elevation model, over-detection of clouds over bright targets, and miss-classification of topographic shadows. This research aims to explore the application of Sentinel-2 imagery for mangrove mapping by comparing two levels of data, including L1C and L2A. L2A is divided into two, namely L2A atmospherically corrected using the Sen2Cor method (L2A_Sen2Cor) and dark object subtraction method (L2A_DOS). The classification scheme was built based on in-situ data containing seven objects: water, clouds, built-up, cloud shadows, bare land, mangroves, and land vegetation using random forest classification. The comparison of each level of data is analyzed based on the spectral signature and accuracy assessment using confusion matrix. The result shows that there are differences in the spectral signature between L1C and L2A data because of atmospheric impacts. L2A outperforms L1C, as shown by the higher coefficient of determination ($R^2$). The accuracy is in the range of 93.7 – 95.4%, with the best accuracy shown by L2A_Sen2Cor.

**Keywords**: Sentinel-2, top of atmosphere, bottom of atmosphere, mangrove, random forest

## 1. Introduction

Remote sensing is one of the technologies that can be used to detect, monitor, and analyze objects and conditions on the Earth's surface [1][2][3]. This technology provides significant benefits by offering spatial and temporal information [4][5][6][7]. The ease of accessing data from sources like as MODIS,

Himawari, Landsat, and Sentinel, along with advancements in computer technology and cloud-based computing, accelerate the processing of remote sensing data [8][9].

Sentinel-2 satellite imagery is a high-resolution multispectral image launched by the European Space Agency. Sentinel-2's mission is to monitor variability on the Earth's surface [10]. To support this mission, Sentinel-2 is equipped with a twin-satellite system in the same orbit. Sentinel-2A was launched on June 23, 2015, and Sentinel-2B on March 7, 2017 [11]. These satellites provide a high-frequency revisit time of five days at the equator, ensuring continuous observation and enabling long-term monitoring and improved change detection. Sentinel-2 carries the Multi-Spectral Instrument (MSI) with 13 spectral bands, including four bands at 10 m, six bands at 20 m, and three bands at 60 m spatial resolution [10]. These specifications make Sentinel-2 imagery an alternative choice for mangrove mapping [12][13][14][15].

Since 2018, Sentinel-2 has released Level-2A products, atmospherically corrected Surface Reflectance (SR) images derived from the associated Level-1C products [10]. The L2A product is processed using the Sen2Cor algorithm, which corrects atmospheric, terrain, and cirrus effects on Top of Atmosphere (TOA) data [10]. This data is suitable for mangrove mapping as it has undergone radiometric correction [16][17]. However, ESA's provided L2A data still experiences overcorrection effects, especially on slopes, due to inaccuracies in the digital elevation model [18].

The identification of mangrove objects using satellite imagery is fundamentally related to the reflectance patterns of each wavelength bouncing off the objects and received by the satellite [12][13][14][15][19]. Mangroves are plants that grow in coastal areas with brackish or saline water conditions [20][21]. Mangroves provide abundant benefits, including habitats for other living organisms, coastal protection, carbon absorption and storage, tourism, and as a source of fuel and building materials for local communities [22][23][24]. The environmental conditions of mangroves in areas with high soil moisture cause different spectral responses compared to terrestrial plants. It makes remote sensing data suitable for mangrove detection. Various studies have utilized Sentinel-2 for mangrove mapping, including mangrove detection [25][26][9][27], mangrove density [28][29], mangrove health [30][19], and mangrove species [31][32].
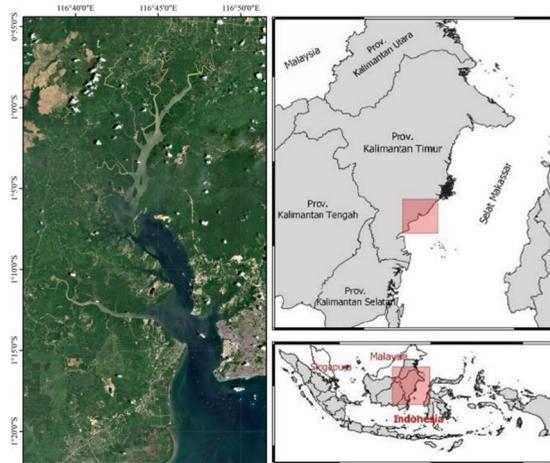
Balikpapan Bay is one of the highly productive bays with a mangrove ecosystem serving as habitat, livelihood source, and ecotourism [33][34][35]. Additionally, massive developments such as the construction of the national capital can directly impact the ecosystem in Balikpapan Bay. The bay also has hilly topography [36], which could potentially be affected by overcorrection in Sentinel-2 L2A data provided by ESA. Furthermore, research related to the utilization of Sentinel-2 for mangrove mapping is still limited in Balikpapan Bay. Therefore, it is crucial to have accurate mangrove maps in this region. The objective of this study is to map mangroves at different data levels, namely, top of atmosphere (L1C) and bottom of atmosphere (L2A), using machine learning methods (random forest) in Balikpapan Bay, East Kalimantan. It is expected that this research will produce an accurate map of mangroves in the study area.

## 2. Materials and Methodology

### 2.1 Research Sites

Balikpapan Bay, East Kalimantan, geographically is located between 0.5' to 1.5' South Latitude and 116.3' to 116.57' East Longitude (Figure 1). This bay provides significant economic benefits for East Kalimantan as a public and private port for fishing and mining activities [33]. Furthermore, the bay is a habitat for an mangroves ecosytem that covers 16,800 hectares [37] with 21 species, including *Rhizophora apiculata*, *Rhizophora mocronata*, *Sonneratia alba*, *Acrosticum aureum*, *Ardisia sp.*, *Avicennia marina*, *Bruguiera gymnorhiza*, *Ceriops tagal*, *Dillenia suffruticosa*, *Dysoxylum sp.*, *Flagellaria sp.*, *Glochidion littorale*, *Guioa sp.*, *Heritiera littoralis*, *Lumnitzera littorea*, *Nypa fruticans*, *Pandanus odoratissima*, *Pouteria sp.*, *Xylocarpus granatum*, *Cerbera manghas* [38], dan *Camptostemon philippinensis* [39]. According to the International Union for Conservation of Nature (IUCN) Red List, *Camptostemon philippinensis*, a vulnerable mangrove species, is present in Lango Village [39]. Moreover, this bay is renowned for its unique biodiversity, serving as potential ecotourism,
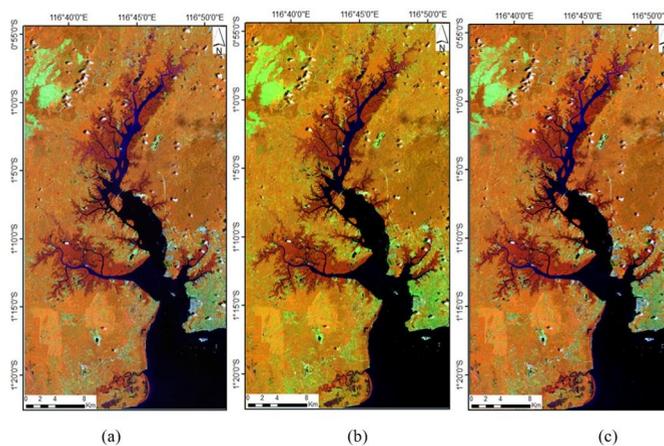
including Lesser Adjutant Stork (*Leptoptilos javanicus*), Proboscis Monkey (*Nasalis larvatus*), Irrawaddy Dolphin (*Orcaella brevirostris*), Green Turtle (*Chelonia mydas*), and the Hawksbill Turtle [35]. Morphologically, Balikpapan Bay is a semi-closed bay directly facing the Makassar Strait [40]. Balikpapan consists of hilly areas with some level terrain located around the river and the coast [36].



**Figure 1.** Research sites in Balikpapan Bay, Kalimantan Timur

*2.2 Data Collection*

Sentinel-2A imagery with two data levels, L1C and L2A was taken on February 26, 2022 from sentinel-hub.com. L1C represents data that has been geometric and radiometric correction, such as orthorectification and spatial registration using a global reference system [10]. This study separates L2A data into two categories: L2A corrected with Sen2Cor method and L2A with dark object subtraction method (L2A_DOS). L2A_DOS was produced from the corrected L1C using the Semi-Automatic Classification Plugin in QGIS Software. Figure 2 uses a combination of SWIR, NIR, and green to show how mangroves appear at each data level. Mangroves are represented by a dark brown color.



(a)             (b)             (c)

**Figure 2.** Composite bands of SWIR, NIR, Green to display mangroves in Balikpapan Bay which are marked with dark brown color at the data level. a) L1C, b) L2A_DOS, dan c) L2A_Sen2Cor.

L2A_Sen2Cor data is L1C data that has been scene classification and atmospheric correction using the Sen2Cor algorithm [10]. According to the ESA's data quality report from February 2022, there are several limitations associated with L2C_Sen2Cor data, such as the blocky patterns on the scene classification mask that lead to a local over-detection of clouds, some differences occur in the overlap area between adjacent tiles, bluish color in color composite and inaccurate surface reflectance due to inaccuracies of the digital elevation model, corrupted pixels affected by missing or degraded instrument source packets that can affect the surface reflectance of other spectral bands, and discontinuities visible in terrain correction on very flat areas [18]. These limitations can lead to misclassification.
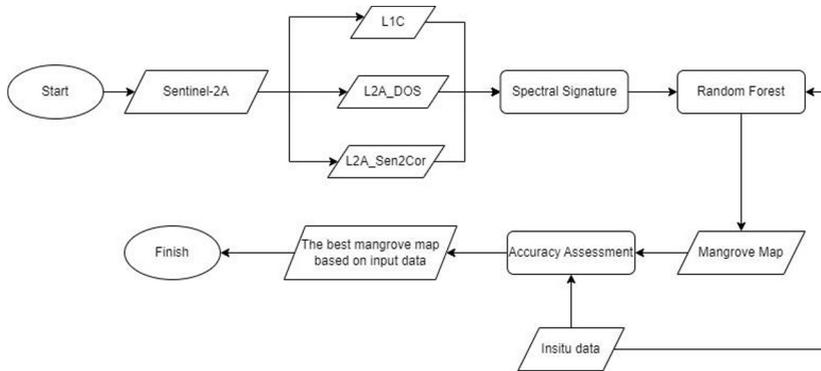
Sentinel-2 has thirteen bands with varying spatial resolutions ranging from 10 m to 60 m. This imagery has a temporal resolution of 10 days, but when both constellations are combined, it can be reduced to 5 days. In this study, 10 bands were utilized to match the number of bands in L2A_Sen2Cor and L2A_DOS data, allowing for a fair comparison (Table 1). In-situ data containing information obtained through field observations on August 21–25, 2023, and sentinel-2 data. Field observations were conducted using an Olympus Tough-6 camera equipped with a Global Positioning System. There are 1400 in-situ data points, with 200 points per object. This data was employed to build a model and validation of mangrove maps obtained from all three data.

**Table 1.** Sentinel-2 specification.

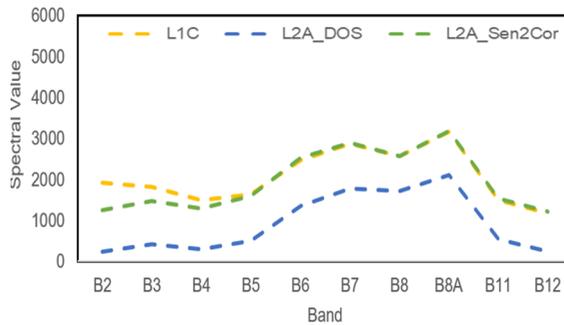| Band | Central Wavelength (nm) | Spatial (m) | Temporal (Days) | Radiometric (Bit) |
|---|---|---|---|---|
| B2 - Blue | 490 | 10 | | |
| B3 - Green | 560 | 10 | | |
| B4 - Red | 665 | 10 | | |
| B5 - Red Edge 1 | 705 | 20 | | |
| B6 - Red Edge 2 | 740 | 20 | 10/5 for combined constellation | 12 |
| B7 - Red Edge 3 | 783 | 20 | | |
| B8 - NIR | 842 | 10 | | |
| B8a - Red Edge 4 | 865 | 20 | | |
| B11 – SWIR1 | 1610 | 20 | | |
| B12 – SWIR2 | 2190 | 20 | | |

*2.3 Image Processing*

Analysis related to the level data was conducted by understanding the spectral signatures of objects. The spectral signatures can be used to determine how each object reacts to different wavelengths. The classification method employed in this study is random forest. Two types of data are needed for random forest classification: training and test sets. This data came from insitu data. The in-situ data is divided into two parts, with 60% used for modeling (training data) and 40% for validation (test data). The classification scheme in this study is based on land cover, consisting of seven classes: water, clouds, built-up, cloud shadows, bare land, mangroves, and land vegetation. The classification results are classed into three primary classes: water, non-mangrove, and mangrove [41], and accuracy assesment is performed using a confusion matrix. In order to accomplish the research goal of analyzing input data for mangrove mapping in Balikpapan based on Sentinel-2A data levels, the processing scheme is illustrated in Figure 3.
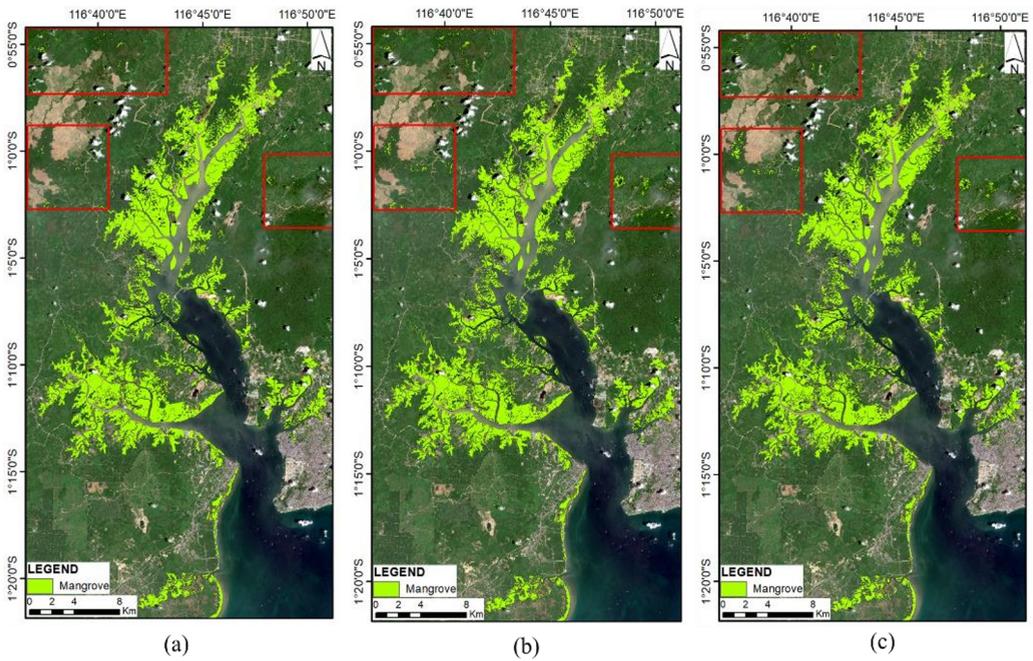
**Figure 3.** The research flowchart

## 3. Results and Discussion

The spectral signatures of each data level are used to examine understanding connected to the data levels (Figure 4). This signatures is formed due to the interaction between wavelengths and objects on the Earth's surface. The spectral signatures of the three data sets are identical in pattern, but the digital values vary escpecially L2A_DOS. L1C and L2A_Sen2Cor have same digital values in Band 5 through 12 but because of the atmospheric influence, there are variances in blue, green, and red band. Based on the interaction of wavelengths with mangroves, the low values for the blue and red bands are though to be caused by absorption and usage by chlorophyll for photosynthesis, reflecting the green and NIR bands, [42][43].



**Figure 4**. Spectral signatures of mangrove. Colors represent data levels. Yellow for L1C, blue for L2A-DOS, and green for L2A_Sen2Cor.

The mangrove map based on random forest classification for each data level are displayed in Figure 5. Spatially, it can be observed that the three datasets do not exhibit significant differences, but misclassifications are still evident in all three datasets. The two main causes of misclassifications are land vegetation and cloud shadows being classified as mangrove. More misclassifications are found in the L2A data, indicating that atmospheric correction increases the degree of uncertainty in the mangrove map and leads to higher levels of misclassification for non-mangrove objects [44]. The spatial distribution suggests that mangrove mapping on L1C data using random forest technique produces more representative results than L2A. When using remote sensing data for mapping, misclassifications are expected, but these can be minimized by eliminating objects through an understanding-based approach related to the objects and study locations [1][45][2]. In this study, as a case study, mangroves found outside coastal areas can be eliminated to obtain more accurate mangrove map.

**Figure 5**. Mangrove map in Balikpapan Bay. Light green represent mangrove.
a) L1C, b) L1C_DOS, dan c) L2A

The utilization of remote sensing technology is considered effective for mapping the extent of mangroves because it can reduce costs and time as well as lower the risk, especially in study areas like Balikpapan Bay inhabited by crocodiles. In this study, random forest classification was employed to generate a mangrove map in Balikpapan Bay. Based on accuracy assesment using confusion matrix shown in Table 2, random forest classification using the three datasets demonstrated an overall accuracy of 93.7%–95.4% and a kappa accuracy of 92.7%–94.7%. The accuracy ranking from highest to lowest is as follows: L2A_Sen2Cor, L2A_DOS, and L1C. Based on accuracy, L2A is superior to L1C. Research related to the utilization of Sentinel-2 for mangrove mapping is still limited in Balikpapan Bay, so a direct comparison cannot be made. However, the accuracy that this study produced can match that of earlier studies conducted in different places using the same satellite and methods [31][26].
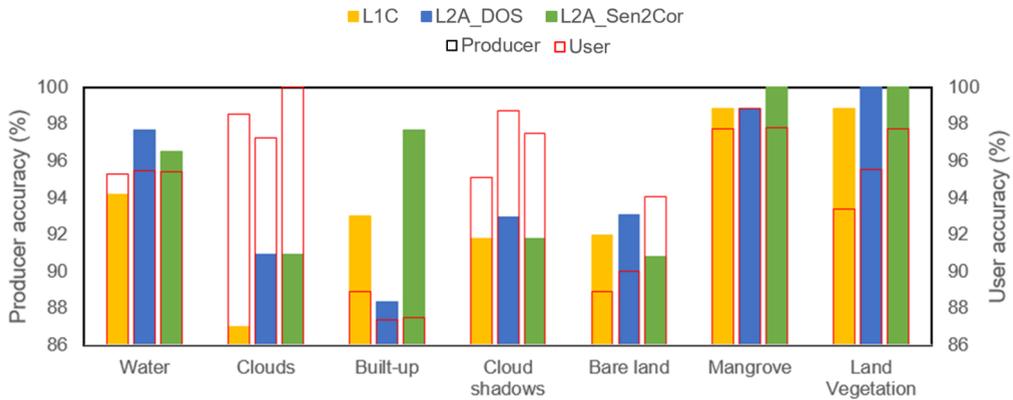
It is necessary to examine each object's distribution using producer and user accuracy (UAs and PAs) to know accuracy of each object. The overall accuracy of L1C data is 93.7%, which is less accurate than L2A data. The PAs are 94.18%, 87.01%, 93.02%, 91.76%, 91.95%, 98.86%, 98.83% for water, cloud, built-up, cloud shadows, bare land, mangrove, land vegetation classes, respectively. The UAs are 95.29%, 98.52%, 88.89%, 95.12%, 88.89%, 97.75%, 93.40% for the classes in the same order. In L2A_DOS, the overall accuracy is 94.6%. The PAs 97.675, 90.90%, 88.37%, 92.94%, 93.10%, 98.86%, and 100% for water, cloud, built-up, cloud shadows, bare land, mangrove, and land vegetation classes, respectively. Meanwhile, the UAs are 95.45%, 97.22%, 87.35%, 98.75%, 90.00%, 98.86%, and 95.55% for the classes in the same order. In contrast to the other two datasets, L2A_Sen2Cor has the highest overall accuracy (95.4%). The PAs are 96.51%, 90.90%, 97.67%, 91.76%, 90.80%, 100%, and 100% for water, cloud, built-up, cloud shadows, bare land, mangrove, and land vegetation classes, respectively. The UAs are 95.40%, 100%, 87.50%, 97.50%, 94.04%, 97.77%, and 97.72%. In comparison to the other two datasets, L2A data offers superior producer and user accuracy based on the precision of each object, particularly mangrove objects.

**Tabel 2**. Accuracy Assesment

| Reference | Water | Cloud | Built-up | Cloud Shadows | Bare land | Mangrove | Land vegetation | Total | Producer accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Map Class **Data 1: L1C** | | | | | |
| Water | 81 | 0 | 0 | 1 | 4 | 0 | 0 | 86 | 94.18 |
| Cloud | 0 | 67 | 5 | 1 | 0 | 0 | 4 | 77 | 87.01 |
| Built-up | 0 | 0 | 80 | 0 | 6 | 0 | 0 | 86 | 93.02 |
| Cloud Shadows | 4 | 0 | 0 | 78 | 0 | 1 | 2 | 85 | 91.76 |
| Bare land | 0 | 1 | 5 | 0 | 80 | 1 | 0 | 87 | 91.95 |
| Mangrove | 0 | 0 | 0 | 1 | 0 | 87 | 0 | 88 | 98.86 |
| Land vegetation | 0 | 0 | 0 | 1 | 0 | 0 | 85 | 86 | 98.83 |
| Total | 85 | 68 | 90 | 82 | 90 | 89 | 91 | 595 | |
| User accuracy (%) | 95.29 | 98.52 | 88.89 | 95.12 | 88.89 | 97.75 | 93.40 | | OA= 93,7 Kappa= 92,7 |
| | | | | **Data 2: L2A_DOS** | | | | | |
| Water | 84 | 0 | 0 | 1 | 1 | 0 | 0 | 86 | 97.67 |
| Cloud | 0 | 70 | 5 | 0 | 1 | 0 | 1 | 77 | 90.90 |
| Built-up | 0 | 2 | 76 | 0 | 7 | 0 | 1 | 86 | 88.37 |
| Cloud Shadows | 4 | 0 | 0 | 79 | 0 | 1 | 1 | 85 | 92.94 |
| Bare land | 0 | 0 | 6 | 0 | 81 | 0 | 0 | 87 | 93.10 |
| Mangrove | 0 | 0 | 0 | 0 | 0 | 87 | 1 | 88 | 98.86 |
| Land vegetation | 0 | 0 | 0 | 0 | 0 | 0 | 86 | 86 | 100 |
| Total | 88 | 72 | 87 | 80 | 90 | 88 | 90 | 595 | |
| User accuracy | 95.45 | 97.22 | 87.35 | 98.75 | 90.00 | 98.86 | 95.55 | | OA= 94,6 Kappa= 93,7 |
| | | | | **Data 3: L2A_Sen2Cor** | | | | | |
| Water | 83 | 0 | 0 | 2 | 1 | 0 | 0 | 86 | 96.51 |
| Cloud | 0 | 70 | 4 | 0 | 3 | 0 | 0 | 77 | 90.90 |
| Built-up | 0 | 0 | 84 | 0 | 1 | 0 | 1 | 86 | 97.67 |
| Cloud Shadows | 4 | 0 | 0 | 78 | 0 | 2 | 1 | 85 | 91.76 |
| Bare land | 0 | 0 | 8 | 0 | 79 | 0 | 0 | 87 | 90.80 |
| Mangrove | 0 | 0 | 0 | 0 | 0 | 88 | 0 | 88 | 100 |
| Land vegetation | 0 | 0 | 0 | 0 | 0 | 0 | 86 | 86 | 100 |
| Total | 87 | 70 | 96 | 80 | 84 | 90 | 88 | 595 | |
| User accuracy | 95.40 | 100 | 87.50 | 97.50 | 94.04 | 97.77 | 97.72 | | OA= 95.40 Kappa= 94,7 |

We used producer and user accuracy to determine the misclassification in Figure 6. Producer accuracy (PA) indicates the percentage of truth that field sample data will be correctly classified in the image, while user accuracy (UA) indicates the percentage of probability that map users will find the correct information in the field [46]. If the producer's accuracy value is smaller than the user's accuracy in a class, that class tends to be overestimated, otherwise it tends to be underestimated. The three data agreed that that build-up and land vegetation are underestimated while cloud and cloud shadow are overestimated. However, if we concentrate on mangroves, we can observe that L2A_DOS has a comparable value on PA and UA while L1C and L2A_sen2cor are underestimated.

Based on spatial distribution, L1C data shows more representative results compared to L2A data. L2A data shows more misclassifications than L1C because of atmospheric correction, which raises the level of uncertainty in the mangrove map [44]. However, L2A_Sen2Cor shows better accuracy than the other two datasets when taking into account both overall accuracy and objects accuracy. There are no misclassifications caused by the limitation of Sentinel-2 DEM in hilly area, as reported in the ESA data quality report [18].

**Figure 6**. Comparison between producer and user accuraccy. Color represent data level. Yellow for L1C, blue for L2A-DOS, and green for L2A_Sen2Cor.

### 4. Conclusion

The overall accuracy of the mangrove map in Teluk Balikpapan using the three datasets is 93.7% to 95.4%, with the highest accuracy shown by L2A_Sen2Cor, which has better producer and user accuracy of each object compared to the other level data. However, based on the spatial distribution of mangroves, atmospheric correction leads to increased misclassification in L2A data. Misclassifications due to the limitations of the Sentinel-2 DEM are not evident in this study. For the specific case like this research, if the main target is a mangrove map, then L1C data is more relevant for understanding how accurately mangrove locations are identified in the images. However, if the goal is to obtain information about how accurately mangroves are classified, then L2A_Sen2Cor data can be used.

### Acknowledgement

### References

[1]   Jensen JR. *Remote Sensing of the Environment: An Earth Resource Perspective*. Pearson Education, 2007.
[2]   Lillesand TM, Kiefer RW, and Chipman JW. *Remote Sensing and Image Interpretation*. John Wiley & Sons, Inc, 2014.
[3]   Lu Y, and Wang L. The Current Status, Potential and Challenges Of Remote Sensing for Large-Scale Mangrove Studies. *Int J Remote Sensing*, vol. 4318, 6824-6855, 2022.
[4]   Kuenzer C, Bluemel A, Gebhardt S, Quoc T V, and Dech S. Remote Sensing of Mangrove Ecosystems. *A Rev Remote Sens*, vol. 3:878–928, 2011.
[5]   Pham T, Xia J, Ha N, Bui D, Le N, and Tekeuchi WA. A Review of Remote Sensing Approaches for Monitoring Blue Carbon Ecosystems: Mangroves, Seagrasses, and Salt Marshes during 2010–2018. *Sensors*, 19, 1933, 2019, https//doi/103390/S19081933.
[6]   Maurya K, Mahajan S, and Chaube N. Remote Sensing Techniques: Mapping and Monitoring of Mangrove Ecosystem—a Review. *Complex Intell Syst*, 72797–2818, 2021, https//doi/101007/S40747-021-00457-Z 2021.
[7]   Winarso G, Rosid MS, Kamal M, Asriningrum W, Margules C, and Supriatna J. Comparison of Mangrove Index (MI) and Normalized Difference Vegetation Index (NDVI) for the Detection of

Degraded Mangroves in Alas Purwo Banyuwangi and Segara Anakan Cilacap, Indonesia. *Ecol Eng*, vol. 197:107119, 2023, https://doi.org/10.1016/j.ecoleng.2023.107119.

[8]     Amani M, Ghorbanian A, Ahmadi SA, Kakooei M, Moghimi A, Mirmazloumi SM, et al. Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. *IEEE J Sel Top Appl Earth Obs Remote Sens,* vol. 13, 2020.

[9]     Ghorbanian A, Zaghian S, Asiyabi RM, Amani M, Mohammadzadeh A, and Jamali S. Mangrove Ecosystem Mapping using Sentinel-1 and Sentinel-2 Satellite Images and Random Forest Algorithm in Google Earth Engine. *Remote Sens*, vol. 13:1–18, 2021, https://doi.org/10.3390/rs13132565.

[10]    ESA. Sentinel-2 User Handbook. European Space Agency, 2015.

[11]    ESA.          About          the          launch,          2022, https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2/About_the_launch#:~:text=Sentinel-2A was launched on,local time on 6 March).

[12]    Hariyanto T, Pribadi CB, and Atsilah IS. Analisis Hasil Identifikasi Persebaran Mangrove Berdasarkan Algoritma Normalized Difference Vegetation Index dan Mangrove Vegetation Index Menggunakan Citra Satelit Sentinel-2 (Studi Kasus: Taman Nasional Alas Purwo). *Geoid*, vol. 18:285,2023, https://doi.org/10.12962/j24423998.v18i2.13854.

[13]    Damsir D, Ansyori A, Yanto Y, Erwanda S, and Purwanto B. Pemetaan Areal Mangrove Di Provinsi Lampung Menggunakan Citra Sentinel 2-a dan Citra Satelit Google Earth. *J Pengabdi Kolaborasi dan Inov IPTEKS*, vol. 1:207–16, 2023, https://doi.org/10.59407/jpki2.v1i3.37.

[14]    Safitri F, Adrianto L, and Nurjaya IW. Pemetaan Kerapatan Ekosistem Mangrove menggunakan Analisis Normalized Difference Vegetation Index di Pesisir Kota Semarang. *J Kelaut Trop*, vol. 26:399–406, 2023, https://doi.org/10.14710/jkt.v26i2.18173.

[15]    Dharma F, Aulia A, Shubhan F, and Ridwana R. Pemanfaatan Citra Sentinel - 2 dengan Metode NDVI untuk Perubahan Kerapatan Vegetasi Mangrove di Kabupaten Indramayu. *J Pendidik Geogr Undiksha*, vol. 10:155–65, 2022.

[16]    Padró JC, Muñoz FJ, Ávila LÁ, Pesquer L, and Pons X. Radiometric Correction of Landsat-8 and Sentinel-2A Scenes using Drone Imagery in Synergy with Field Spectroradiometry. *Remote Sens*, vol. 10, 2018, https://doi.org/10.3390/rs10111687.

[17]    Kganyago M, Ovakoglou G, Mhangara P, Alexandridis T, Odindi J, Adjorlolo C, et al. Validation of Atmospheric Correction Approaches for Sentinel-2 under Partly-Cloudy Conditions in an African Agricultural Landscape, *Remote Sensing of Clouds and the Atmosphere XXV*, 2020, https://doi.org/10.1117/12.2572293.

[18]    ESA. Data Quality Report - MSI L2A - May 2022. Sentin Online -Data Prod Qual Reports 2022, 2022.

[19]    Hidayah Z, Rachman HA, and As-Syakur AR. Pemetaan Kondisi Hutan Mangrove di Kawasan Pesisir Selat Madura dengan Pendekatan Mangrove Health Index Memanfaatkan Citra Satelit Sentinel-2. *Maj Geogr Indones*, vol. 37:1, 2023, https//doi.org/1022146/Mgi78136 n.d.

[20]    Hogarth P. The Biology of Mangroves and Seagrasses, 2007.

[21]    Gunawan B, Purwanti S, Hidayati S, Pratiwi YI, and Ali M. Aksi Restorasi Penanaman Mangrove dalam Memitigasi Bencana. *J Pengabdi Kpd Masy*, vol. 3:1–10, 2022.

[22]    Alongi D. Present State and Future of The World's Mangrove Forests. *Environ Conserv*, Vol. 29, 331, 2002.

[23]    Subagiyo L, Herliani, Sudarman, Haryanto Z. Literasi Hutan Tropis Lembab dan Lingkungannya. vol. 53, 2019.

[24]    Nasution T. Daya Dukung Hutan Mangrove Pangkal Babu pada Kelimpahan Sumberdaya Ikan dan Ekonomi Masyarakat Desa Tungkal Satu Tanjung Jabung Barat. *J Natur Indones*, 2023.

[25]    Baloloy AB, Blanco AC, Ana RRCS, and Nadaoka K. Development and Application of a New Mangrove Vegetation Index (MVI) for Rapid and Accurate Mangrove Mapping. *ISPRS J Photogramm Remote Sens*, vol. 166: 95-117, 2020.

[26]    Chen N. Mapping Mangrove in Dongzhaigang, China using Sentinel-2 Imagery. *J Appl Remote*

*Sens*, vol. 14(1), 014508, 2020, https//doi.org/101117/1JRS14014508.

[27] Sharifi A, Felegari S, and Tariq A. Mangrove Forests Mapping using Sentinel-1 and Sentinel-2 Satellite Images. *Arab J Geosci*, vol. 15, 1593, 2022, https//doi.org/101007/S12517-022-10867-Z.

[28] Muhsoni FF, Sambah A., Mahmudi M, and Wiadnya DG. Comparison of Different Vegetation Indices for Assessing Mangrove Density Using Sentinel-2 Imagery. *Int J Geomate*, vol. 14: 42-51, 2018, https//doi.org/1021660/2018457177 ISSN 2186-2982 (Print), 2186-2990 (Online).

[29] Samsuri, Zaitunah A, Meliani S, Syahputra OK, Budiharta S, Susilowati A, et al. Mapping of Mangrove Forest Tree Density using Sentinel-2A Satelit Image in Remained Natural Mangrove Forest of Sumatra Eastern Coastal. *IOP Conf Ser Earth Environ Sci*, vol. 912, 2021.

[30] Akbar MR, Arisanto PAA, Sukirno BA, Merdeka PH, Priadhi MM, and Zallesa S. Mangrove Vegetation Health Index Analysis by Implementing NDVI (Normalized Difference Vegetation Index) Classification Method on Sentinel-2 Image Data Case Study: Segara Anakan, Kabupaten Cilacap. *IOP Conf Ser Earth Environ Sci*, vol. 584:0–7, 2020, https://doi.org/10.1088/1755-1315/584/1/012069.

[31] Wang D, Wan B, Qiu P, Su Y, Guo Q, Wang R, et al. Evaluating the Performance of Sentinel-2, Landsat 8 and Pléiades-1 in Mapping Mangrove Extent and Species. *Remote Sens*, 10, 1468, 2018, https//doi,org/103390/Rs10091468.

[32] Pham TD, Xia J, Thang Ha N, Tien Bui D, Nhu Le N, and Tekeuchi W. A Review of Remote Sensing Approaches for Monitoring Blue Carbon Ecosystems: Mangroves, Seagrasses And Salt Marshes during 2010–2018. *Sensors (Switzerland)*, vol. 19, 2019, https://doi.org/10.3390/s19081933.

[33] Lahjie AM, Nouval B, Lahjie AA, Ruslim Y, and Kristiningrum R. Economic Valuation from Direct Use of Mangrove Forest Restoration in Balikpapan Bay, East Kalimantan, Indonesia. *F1000Research*, vol. 8:9, 2019, https://doi.org/10.12688/f1000research.17012.1.

[34] Sayektiningsih T. Community Perceptions of Impacts of Ecotourism and Its Implications on Ecotourism Development in the Balikpapan Bay, East Kalimantan. *J Wasian*, vol. 6:57–67, 2019, https://doi.org/10.20886/jwas.v6i1.4666.

[35] Willard K, Aipassa MI, Sardjono MA, Rujehan, Ruslim Y, and Kristiningrum R. Locating the Unique Biodiversity of Balikpapan Bay as an Ecotourism Attraction in East Kalimantan, Indonesia. *Biodiversitas*, vol. 23:2342–57, 2022, https://doi.org/10.13057/biodiv/d230512.

[36] Harfadli MM, Ulimaz M. Identification of Flood Vulnerable Zones in Batu Ampar Village, Balikpapan City using Geographical Information System Methods. *IOP Conf Ser Earth Environ Sci*, vol. 623:0–6, 2021, https://doi.org/10.1088/1755-1315/623/1/012031.

[37] Forest Watch Indonesia. IKN dan Teluk Balikpapan, 2023, https://fwi.or.id/ikn-dan-teluk-balikpapan/.

[38] Warsidi & Endayani. Komposis Vegetasi Mangrove di Teluk Balikpapan Provinsi Kalimantan Timur. *J AGRIFOR*, XVI:115–24, 2007.

[39] Sitepu BS, Mukhlisi ARCM, Atmoko T, and Adman BIP. Camptostemon Philippinensis, a New Record of Endangered Mangrove Species in the Balikpapan Bay, East Kalimantan, Indonesia. *F1000Research*, vol. 12:1394, 2023, https://doi.org/1012688/F1000research1408871.

[40] Hermansyah H, Ningsih NS, Nabil, and Tarya A, Syahruddin. Numerical Modeling of Tidal Current Patterns Using 3-Dimensional MOHID in Balikpapan Bay, Indonesia. *J Ilm Perikan Dan Kelautan*, vol. 12(1)9–20, 2020, http//doi.org/1020473/JipkV12i116257.

[41] Hai-Hoa Nguyen, Nghia NH, Nguyen HTT, Le AT, Tran LTN, Duong LVK, et al. Classification Methods for Mapping Mangrove Extents and Drivers of Change in Thanh Hoa Province, Vietnam during 2005-2018, *Forest and Society*, Vol. 4 No. 1, 2020, http://doi.org/1024259/FsV4i19295.

[42] Basheer MA, Kafrawy SB El, Mekawy AA. Identification of Mangrove Plant using Hyperspectral Remote Sensing Data along the Red Sea, Egypt. *Egypt J Aquat Biol Fish Zool Dep Fac Sci Ain Shams Univ Cairo*, vol. 23(1) 27 – 36, 2019.

[43]    Rahmandhana A., Kamal M, and Wicaksono P. Spectral Reflectance-Based Mangrove Species Mapping from WorldView-2 Imagery of Karimunjawa and Kemujan Island, Central Java Province, Indonesia. *Remote Sens*, vol 14, 183, 2020, https//doi.org/103390/Rs14010183.

[44]    Medina-Lopez E. Machine Learning and the End of Atmospheric Corrections: A Comparison between High-Resolution Sea Surface Salinity in Coastal Areas from Top and Bottom of Atmosphere Sentinel-2 Imagery. *Remote Sens*, vol. 12(18), 2924, 2020, https//doi.org/103390/Rs12182924.

[45]    Blaschke T. Object-Based Image Analysis for Remote Sensing. *ISPRS J Photogramm Remote Sensing*, 65(1), 2-16, 2010.

[46]    Congalton RG. A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sens Environ*, vol. 37:35–46, 1991, https://doi.org/10.1016/0034-4257(91)90048-B.