ESTIMATION OF MANGROVE BIOMASS USING LANDSAT DATA ON GOOGLE EARTH ENGINE (GEE) PLATFORM

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ABSTRACT: Segara Anakan is one of 3.5 million hectares of Indonesian mangrove forests, and local deforestation has affected the mangrove area leading to the shrinking and decreased biomass of mangrove forests. For management of the mangrove forest is needed information of the biomass in Segara Anakan area. The objective of this study to estimate the biomass using Landsat data time series on the Google Earth Engine (GEE) platform. The methodology including built a Landsat normalized difference vegetation index (NDVI) time series in 1990, 1995, 2003, and 2019 and estimating the biomass in GEE platform, and after that we did the validation with field data. The result showed that the trend of biomass estimation per year in 1990 was 12.8 ton/ha, and it has been increased in 1995 around 14,3 ton/ha, decreased in 2003 with 11.2 ton/ha, and in 2019 was 11.29 ton/ha. The validation showed with R^2 = 0.8, which means that the biomass estimation from imagery have a strong correlation with field data.

1. BACKGROUND

Biomass is directly related to climate change and has an essential part in the carbon cycle. The total organic matter generated by a plant, expressed in tons of dry weight per unit area, is known as the biomass (Issa et al., 2020). In its early stages, biomass measurement included all biological biomass above and below the ground (Pham et al., 2019). Biomass estimation can be done with three approaches, include modeling, direct measurement in the field or terrestrial, and Remote Sensing (Soni. Darmawan et al., 2019; Pham et al., 2019).

The Normalized Difference Vegetation Index (NDVI) approach was used to estimate biomass in this study. The above-ground biomass of green vegetation has been found to be significantly related to the spectral reflectance of the red and near infrared bands (NIR) (Baloloy et al., 2018). The mathematical combination of red and NIR wavelengths is calculated as a vegetation index that gets advantage of wavelength ability in vegetation reflection (Baloloy et al., 2018; Hernawati & Darmawan, 2018). Several vegetation indices which are sensitive to biomass fluctuations are now available, and comparison studies are being carried out to determine the ideal vegetation index for biomass mapping (Ahmad et al., 2021). To develop spatial models of mangrove biomass, satellite imagery, field measurements, and allometric equations were integrated (Bindu et al., 2020). Because the vegetation index method is not enough to estimate biomass distribution, an allometric equation model is required (Rodríguez-Veiga et al., 2017). Allometric equations are promising for measuring C stocks in biomass because it enables the use of existing and easily measurable variables such as tree diameter, height, or bole volume. Allometric equations offer a method for calculating the biomass of individual trees of various sizes within a population based on tree dimensions. Equations are used to plot inventory data to generate ground-based estimations of plot biomass density (Keenan, 1999). Biomass estimate has been widely used with modeling allometric equations based on the correlation between vegetation index and biomass, such as Rianzani et al (2018) used allometric because allometric equation has a modest average difference between biomass and biomass from field measurements. Correlation was obtained through regression analysis which provided predictive values for the dependent variable (component biomass) (Darmawan et al., 2015), the error of the correlation, and the assumption of confidence in the prediction, for a certain value of the independent value (measured tree dimension) (Darmawan et al., 2016). Least squares linear regression is defined as a straight line that results in a slight difference in the observed value from the expected value (Keenan, 1999).

Google Earth Engine is a cloud-based platform for planetary-scale geospatial analysis that brings Google's massive computational capabilities to bear on a variety of high-impact societal issues including deforestation, drought, disaster, disease, food security, water management, climate monitoring and environmental protection. After the USGS opened access to its records of Landsat imagery in 2008, Google saw an opportunity to use its cloud computing resources to allow records of Landsat imagery to be accessed and processed over its online system (Patela et al., 2015). This has enabled users to reduce processing times in analyses of Landsat imagery and make global scale Landsat projects more feasible (Zeng et al., 2020). The 30 m spatial and multispectral resolution is ideal for defining urban areas, and its revisit time is sufficient for monitoring applications (Hu et al., 2020). It is unique in the field as an integrated platform designed to empower not only traditional remote sensing scientists, but also a much wider audience that lacks the technical capacity needed to utilize traditional supercomputers or large-scale commodity cloud computing resources (Gorelick et al., 2017).

In this study, four Landsat data sets from 1990 to 2019 were used to compute NDVI and develop allometric models to find that different in biomass distribution pattern. This research provided use of Google Earth Engine to assist with multitemporal data processing.

2. Material and Method

2.1 Study Area

Study area of this study is in in the Segara Anakan mangrove conservation area. Segara Anakan is a big lagoon on the southern shore of Java Island, on the boundary between the provinces of West Java and Central Java (White et al., 1989). Segara Anakan is a lagoon in Cilacap Regency that connects Java Island with Nusakambangan Island. The Segara Anakan region is an intersection of 3 (three) large rivers, specifically the Citanduy, Cibereum, and Cikonde, as well as many smaller rivers. This region also shows the connection for economic movement and public water transportation from Cilacap to Pangandaran. Segara Anakan is a unique water area, because it is dominated by a very wide expanse of mangrove forest. This place is one of the natural laboratories for researchers at domestic and international from various disciplines including biology, geology, physics, social, economics, culture, and law (White et al., 1989).

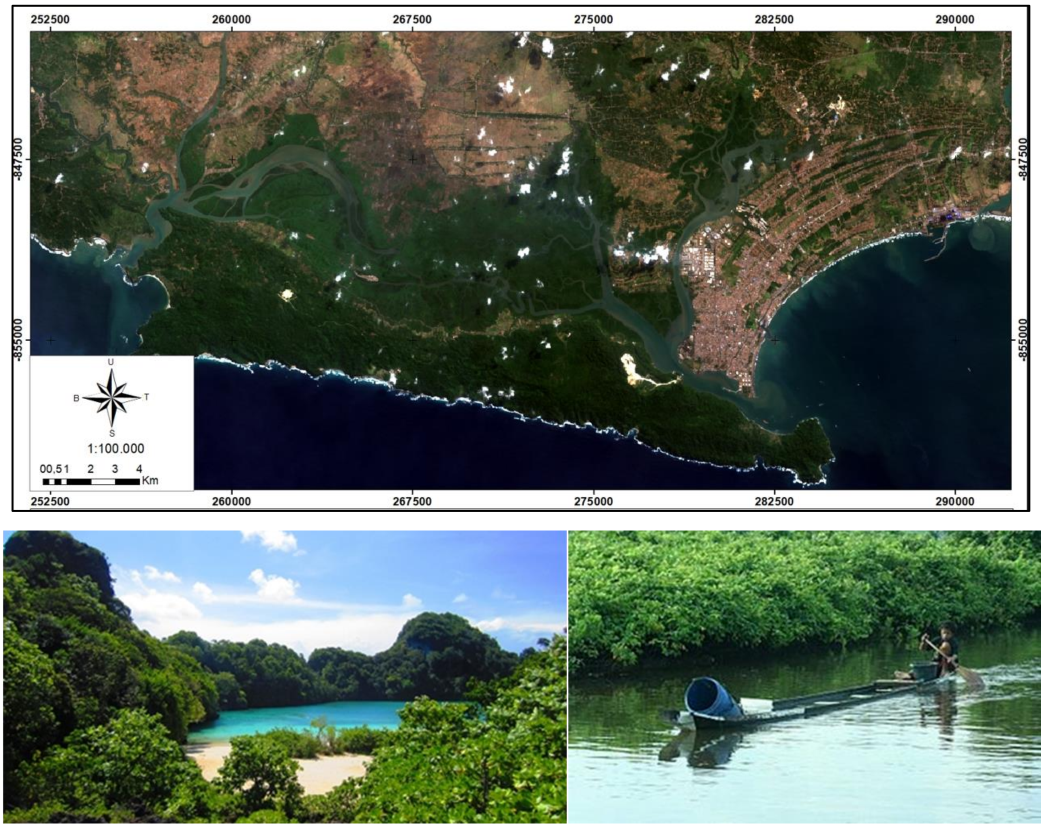

Figure 1. Study Area in Mangroves Conservation Segara Anakan

2.2 Data

Data includes Landsat 5 TM Collection 1 Tier 1 TOA Reflectance Satellite Imagery recording July 1990 and June 1995, Landsat 7 Collection 1 Tier 1 TOA Reflectance recording January 2003, and Landsat 8 Collection 1 Tier 1 TOA Reflectance recording July 2019 all using path/row 121 /065 from USGS (US Geological Survey) which has been integrated with Google Earth Engine.

2.3 Methodology

The Pre-Processing process is a conditioning process that ensures the imagery to be utilized has geometrically and radiometrically correct data. In this research, Google Earth Engine is used, which has been carefully adjusted for all datasets in the cloud, as well as landsat top of atmospheric data from Google Earth Engine. Landsat top of atmosphere is a landsat picture that has been radiometrically adjusted to remove atmospheric disturbances by converting the digital number to a reflectance value.

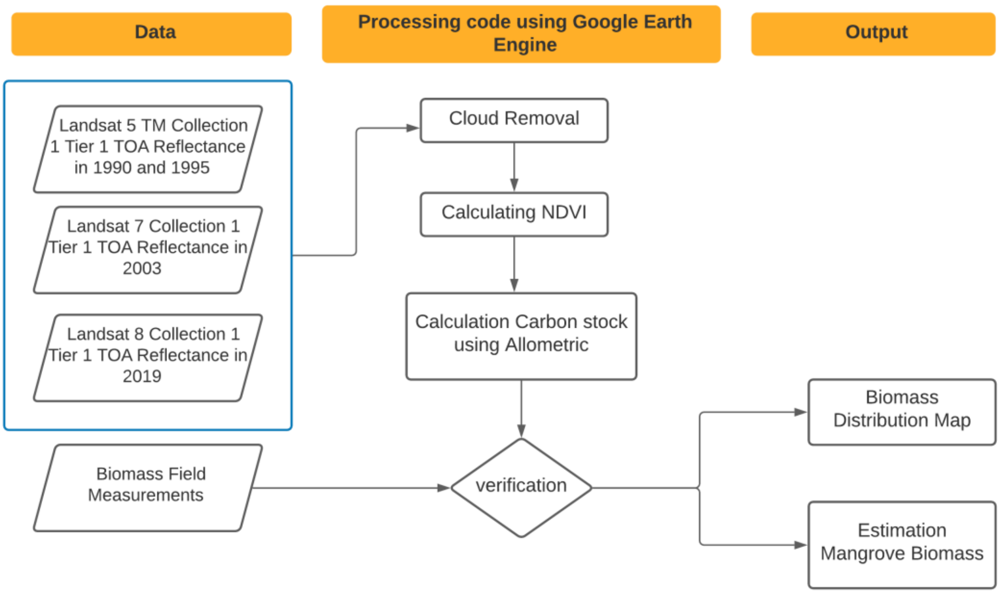

Figure 2. Methodology

2.3.1 Pre-processing

We masked the images that had more than 30% cloud coverage over the studied area in the pre-processing step, then masked out all detected cloudy pixels. Identify mangroves to determine the boundaries of mangrove forests, to find out which are mangroves and other vegetation, we use a combination of NIR, SWIR and Red Bands to separate land and aquatic vegetation, and separate land and water. All the other tasks used Google Earth Engine's Code Editor.

2.3.2 Calculating NDVI value

The Normalized Difference Vegetation Index (NDVI) is derived using satellite data bands. It provides an estimate of the health and density of vegetation at a pixel based on the intensity of reflected sunlight from the visible (VIS) (0.4-0.7m) and near infrared (NIR) (0.7-1.1m) spectrums acquired by satellite sensors (Zeng et al., 2020). While healthy plant leaves primarily absorb light from the red spectrum (0.63-0.69m) in the process of photosynthesis, utilizing chlorophyll to produce glucose from carbon dioxide and water, their cell walls significantly reflect light from the NIR range (Chen et al., 2017; Hernawati & Darmawan, 2017).

2.3.3 Estimation Mangrove Biomass

For Estimating Mangrove Biomass based on allometric equation model belonging Budi Chandra (2000) from his research he produced 12 models, and we use the rational function model which is considered the best model with R^2 = 82,8% with the following model;

$$W = \frac{30{,}97183 - 56{,}898258\ \mathrm{NDVI}}{1 + 3{,}95247\ \mathrm{NDVI} - 9{,}5673017\ \mathrm{NDVI}^2} \ ; \ R^2 = 82{,}8\%$$

3. RESULT

Biomass estimation using multitemporal Landsat satellite image processing utilizing allometric model equations produces an average annual biomass estimation value of 0.5 - 1 ton/ha, with an increase of approximately 2 tons/ha over the previous year in 1995.

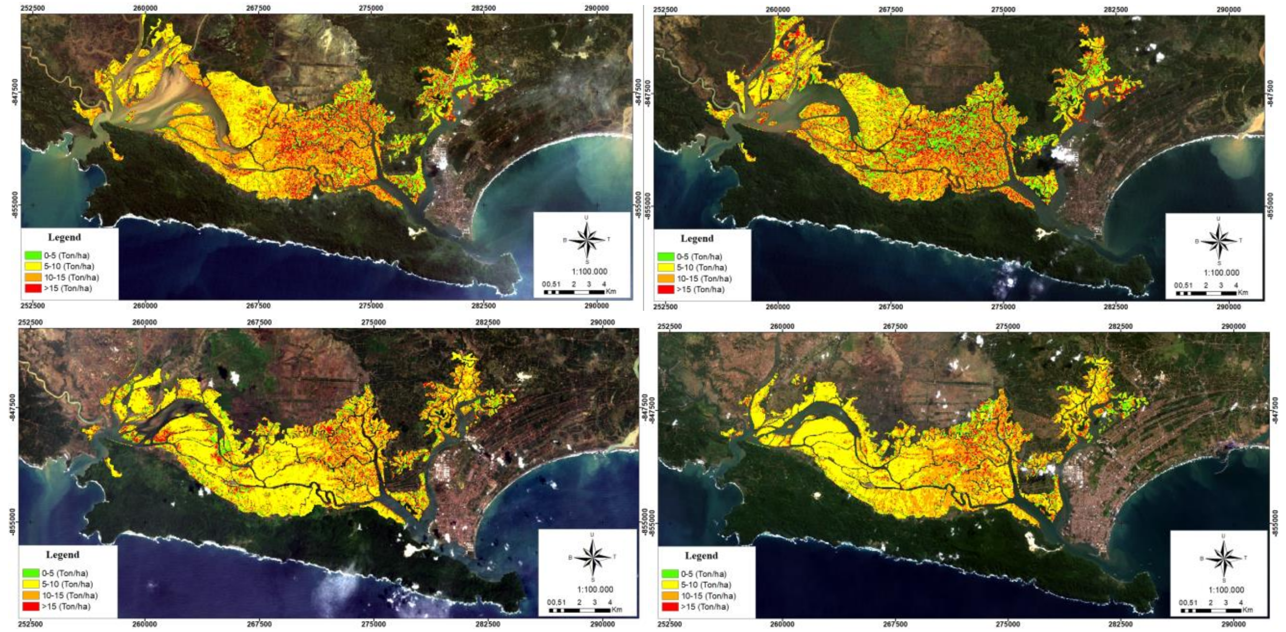

Figure 3. Distribution Of Biomass Results From 1990 To 2019

The estimated biomass production in 1990 was 0.202 tons/ha with a maximum of 103.002 tons/ha and dominated in the range of 5-10 tons/ha with a mangrove forest area of 10621.3 ha. In 1995, biomass estimate produced a biomass estimation value of 0.5 - 1 ton/ha, with an increase of approximately 2 tons/ha, and got a biomass production of 0.202 tons/ha, with a minimum of 0.202 tons/ha and a high of 99.489 tons/ha. In 2003, with an area of 10976.2 ha, dominated in the range of 5-10 tons/ha and 10-15 tons/ha, and produced a biomass output of 0.039 tons/ha and a maximum of 100.393 tons/ha. In 2019, dominated in the range of 5-10 tons/ha with a mangrove forest area of 9952.6 ha and produced a minimum biomass output of 0.000453 tons/ha and a maximum of 100.5 tons/ha with a mangrove forest area of 9596,628 ha.

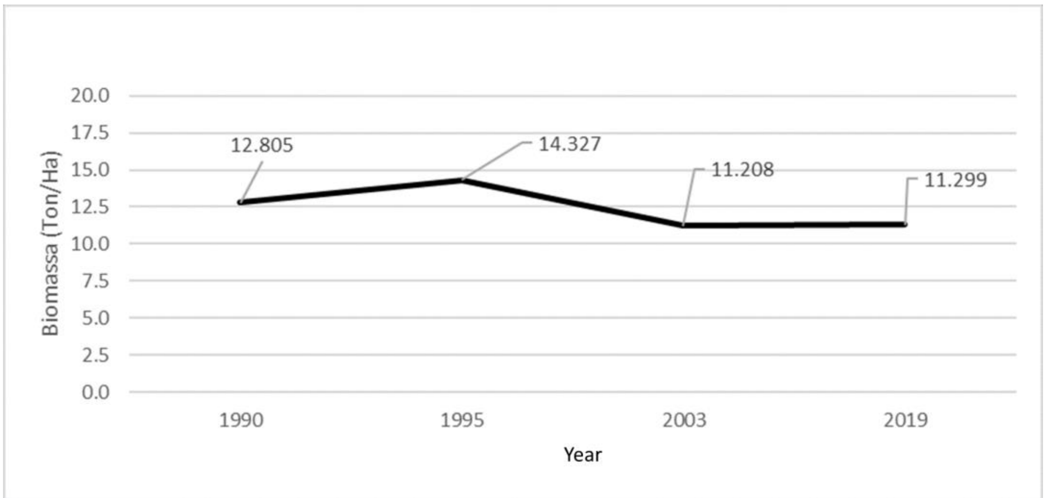

Figure 4. Average Value Of Estimated Biomass Each Year

Mangrove biomass in Segara Anakan is dominated by a biomass value of around 10-15 tons/ha. The average value is obtained by comparing the total of all biomass values. The averaged biomass value is devoid of any anomalies that may have occurred during the biomass computation. The average value of biomass increased significantly in 1995 because of the weather or climatic conditions of that year. According to Glantz (2001), extreme drought and widespread forest fires hit Indonesia in 1995. According to Kurnia and Agdialta's (2020) study, drought produces a reduction in the NDVI value. Rainfall influences the NDVI value, where the higher the rainfall, more the positive the NDVI value and conversely, the lower the rainfall, the more negative the NDVI value. According to Barrett and Curtis (1992), the correlation between NDVI and biomass is not linear (inconsistent), and as a result, the average value of estimated biomass may rise or decrease.

Beside forest fire and rainfall, mangrove in Segara Anakan's condition is exacerbated by high sedimentation rates from the Citandui and Cikonde rivers, which accelerates the loss of the Segara Anakan lagoon as it turns into land. The high sedimentation rate will change the distribution pattern of the seeds and the recolonization, which is caused the NDVI calculation result may inverted by the positive and negative factor (Soni Darmawan et al., 2020).

To verify the estimated biomass value with field data, we look for the difference between the two. Field data obtained by measuring the circumference of the tree and then looking for the diameter of the circumference, biomass calculation by field survey using the formula from Brown (1997) with the equation (1);

$$W = 42{,}69 - 12{,}8\ (D) + 1{,}242\ (D^2) \qquad (1)$$

After getting the difference, we look for the correlation between the estimated value and the field value using linear regression to prove the R^2 value.

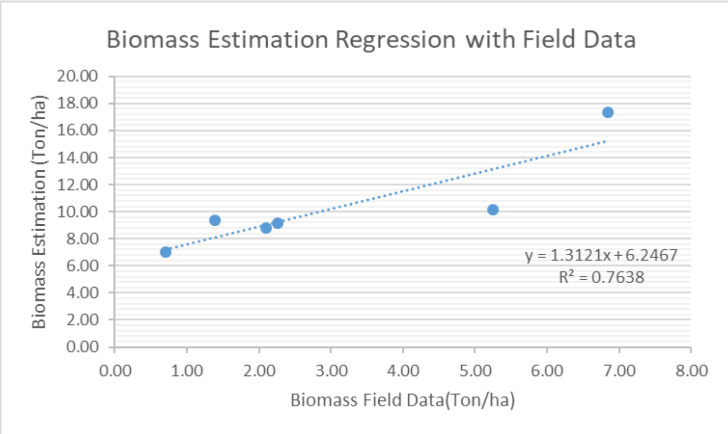

Figure 5. Linear Regression Scatterplot

a mathematical model is obtained with $y = 1{,}3121x + 6{,}2467$ with a value of R^2 around 76.38% which the value of the correlation level is close to R^2 value from the rational function or the estimation model with R^2 = 82,8%.

4. CONCLUSION

Biomass in Cilacap, Segara Anakan According to the mangrove biomass distribution map, the most dominant is in the range of 5-10 tons/ha, and the extent of mangrove forest in Segara Anakan, Cilacap continues to decrease every year, with an area of 9596,628 hectares in 2019. Research study conducted in 1995, the average estimated biomass in Segara Anakan, Cilacap was 14.326754 tons/ha, and the lowest was in 2003, which was 11.208076 tons/ha. During the period 1995-2004, there was an extreme condition within form of a La Nina storm, which caused a change in the NDVI value during the year.

5. REFERENCES

Ahmad, A., Gilani, H., & Ahmad, S. R. (2021). Forest aboveground biomass estimation and mapping through high-resolution optical satellite imagery—a literature review. *Forests*, *12*(7), 1–20. https://doi.org/10.3390/f12070914

Balidoy Baloloy, A., Conferido Blanco, A., Gumbao Candido, C., Jay Labadisos Argamosa, R., Bart Lovern Caboboy Dumalag, J., Lee Carandang DImapilis, Lady, & Camero Paringit, E. (2018). Estimation Of Mangrove Forest Aboveground Biomass Using Multispectral Bands, Vegetation Indices And Biophysical Variables Derived From Optical Satellite Imageries: Rapideye, PlanetScope And Sentinel-2. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *4*(3), 29–36. https://doi.org/10.5194/isprs-annals-IV-3-29-2018

Bindu, G., Rajan, P., Jishnu, E. S., & Ajith Joseph, K. (2020). Carbon stock assessment of mangroves using remote sensing and geographic information system. *Egyptian Journal of Remote Sensing and Space Science*, *23*(1), 1–9. https://doi.org/10.1016/j.ejrs.2018.04.006

Chen, B., Xiao, X., Li, X., Pan, L., Doughty, R., Ma, J., Dong, J., Qin, Y., Zhao, B., Wu, Z., Sun, R., Lan, G., Xie, G., Clinton, N., & Giri, C. (2017). A mangrove forest map of China in 2015: Analysis of time series Landsat 7/8 and Sentinel-1A imagery in Google Earth Engine cloud computing platform. *ISPRS Journal of Photogrammetry and Remote Sensing*, *131*(September), 104–120. https://doi.org/10.1016/j.isprsjprs.2017.07.011

Darmawan, S., Takeuchi, W., Nakazono, E., Parwati, E., Dien, V. T., Oo, K. S., Wikantika, K., & Sari, D. K. (2016). Characterization and spatial distribution of mangrove forest types based on ALOS-PALSAR mosaic 25m-resolution in Southeast Asia. *IOP Conference Series: Earth and Environmental Science*, *37*(1). https://doi.org/10.1088/1755-1315/37/1/012035

Darmawan, Soni., Sari, D. K., Takeuchi, W., Wikantika, K., & Hernawati, R. (2019). Development of aboveground mangrove forests' biomass dataset for Southeast Asia based on ALOS-PALSAR 25-m mosaic. *Journal of Applied Remote Sensing*, *13*(04), 1. https://doi.org/10.1117/1.jrs.13.044519

Darmawan, Soni., Takeuchi, W., Vetrita, Y., Wikantika, K., & Sari, D. K. (2015). Impact of topography and tidal height on ALOS palsar polarimetric measurements to estimate aboveground biomass of mangrove forest in Indonesia. *Journal of Sensors*, *2015*. https://doi.org/10.1155/2015/641798

Darmawan, Soni, Sari, D. K., Wikantika, K., Hernawati, R., Tridawati, A., & Sedu, M. K. (2020). Identification before-after forest fire and prediction of mangrove forest based on Markov-cellular automata in part of Sembilang national park, Banyuasin, south Sumatra, Indonesia. *Remote Sensing*, *12*(22), 1–25. https://doi.org/10.3390/rs12223700

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*(2016), 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hernawati, R., & Darmawan, S. (2018). Change detection analysis using NDVI in Bandung, Indonesia. *Proceedings - 39th Asian Conference on Remote Sensing: Remote Sensing Enabling Prosperity, ACRS 2018*, *2*(October 2018), 1203–1210.

Hernawati, R., & Darmawan, S. (2017). Analisis Kerapatan Vegetasi Berbasiskan Data Citra Satelit Landsat Menggunakan Teknik NDVI di Kota Bandung Tahun 1990 dan 2017. *Seminar Nasional Rekayasa Dan Desain Itenas 2018. Peranan Rekayasa Dan Desain Dalam Percepatan Pembangunan Nasional Berkelanjutan, 4 Desember 2018, Kampus Institut Teknologi Nasional - Bandung.*, 33–39.

Hu, L., Xu, N., Liang, J., Li, Z., Chen, L., & Zhao, F. (2020). Advancing the mapping of mangrove forests at national-scale using Sentinel-1 and Sentinel-2 time-series data with Google Earth Engine: A case study in China. *Remote Sensing*, *12*(19). https://doi.org/10.3390/RS12193120

Issa, S., Dahy, B., Ksiksi, T., & Saleous, N. (2020). A review of terrestrial carbon assessment methods using geo-spatial technologies with emphasis on arid lands. *Remote Sensing*, *12*(12). https://doi.org/10.3390/rs12122008

Keenan, R. J. (1999). *accounting system Review of Allometric Woody Biomass for New South*. *January*.

Patela, N. N., Angiuli, E., Gamba, P., Gaughan, A., Lisini, G., Stevens, F. R., Tatem, A. J., & Trianni, G. (2015). Multitemporal settlement and population mapping from landsatusing google earth engine. *International Journal of Applied Earth Observation and Geoinformation*, *35*(PB), 199–208. https://doi.org/10.1016/j.jag.2014.09.005

Pham, T. D., Yokoya, N., Bui, D. T., Yoshino, K., & Friess, D. A. (2019). Remote sensing approaches for monitoring mangrove species, structure, and biomass: Opportunities and challenges. *Remote Sensing*, *11*(3), 1–24. https://doi.org/10.3390/rs11030230

Rodríguez-Veiga, P., Wheeler, J., Louis, V., Tansey, K., & Balzter, H. (2017). Quantifying Forest Biomass Carbon Stocks From Space. *Current Forestry Reports*, *3*(1), 1–18. https://doi.org/10.1007/s40725-017-0052-5

White, A. T., Martosubroto, P., & Sadorra, M. S. M. (1989). The coastal environmental profile of Segara Anakan-Cilacap, South Java, Indonesia. In *ICLARM Technical Reports* (Vol. 25).

Zeng, H., Wu, B., Wang, S., Musakwa, W., Tian, F., Mashimbye, Z. E., Poona, N., & Syndey, M. (2020). A Synthesizing Land-cover Classification Method Based on Google Earth Engine: A Case Study in Nzhelele and Levhuvu Catchments, South Africa. *Chinese Geographical Science*, *30*(3), 397–409. https://doi.org/10.1007/s11769-020-1119-y