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Testing the influence of spectral resolution for binary change detection accuracies using simulated multispectral bands resampled from hyperspectral data

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Abstract. The ability from remote sensing data to observe the same areas at different times of acquisition is beneficial for change detection analysis. Various sensors from passive to active sensors have been employed. However, the development of satellite hyperspectral sensors brings the premise of a more accurate change detection analysis. Our study aims to test this premise by conducting the binary change detection analysis at different spectral resolution in Central Java Province. The PRISMA datasets were resampled into the spectral resolution of RapidEye (4-bands), Landsat-8 (8-bands), Sentinel-2 (13-bands), and MODIS (19-bands), apart from the original spectral resolution (237-bands) that were used for detecting change using the Principal Component Analysis and K-Means unsupervised analysis methods (PCA-Kmeans). Our results demonstrated that change detection analysis using the RapidEye and Sentinel-2 spectral resolution produced the highest overall accuracies with both showing the same accuracy of 72.04 %. While the original 237 bands produced the accuracy of 65.74 %. This indicated that the detection of major changes in the surface cover can be produced using 4 to 13 bands data. However, hyperspectral data are still potential to be used to detect slight changes in the surface cover, or to perform the unmixing based change detection analysis.

1 Introduction

Change detection analysis is one of the main contributions of remote sensing technology to the study of global environmental and ecological changes. Basically, change detection is a process of a state of an object or phenomenon at different timescales [1-3]. The development of remote sensing technology with spatial, spectral and temporal resolution capabilities is the most capable method in the analysis of change detection, since it is able to observe same areas at different time of acquisition [4]. The change detection analysis using remote sensing data can be performed by using passive system, such as multispectral and hyperspectral dataset, active system, i.e. Synthetic Aperture Radar (SAR) data, or the combination from passive and active remote sensing system.

There are many methods for deriving change information using remote sensing data, but mainly divided into an unsupervised semi-supervised and supervised methods [5] with unsupervised being preferred especially when the ground reference data are limited, while Seydi and Hasanlou [6] divided the methods into 4 main groups: 1.) post-classification methods, 2.) spectral transformation, 3.) direct mult-date classification, and 4.) matched-based procedure. Currently, the main method of change detection is a method at the pixel and sub pixel levels using optical remote sensing data, however, multispectral image data with mixed pixels has limitations where the loss of subtle spectral changes can only be captured at the subpixel level [7]. Along with the development of remote sensing technology, the emergence of various images with various spectral resolutions from those with a wide range to more detailed ones brings great potential in land cover interpretation and monitoring [8]. However, the current development of satellites has a tendency if the spatial resolution is high, the spectral resolution is low, and vice versa [9].

In addition, the development of various satellite hyperspectral sensors, such as PRISMA Hyperspectral [10, 11], brings more options for conducting change detection analysis. The satellite hyperspectral data has been used

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for many applications, including land cover mapping [12] and change detection analysis [5, 13]. This variety of spectral resolution may bring different results when being used for change detection analysis, although the study of spectral resolution effect to the change detection accuracy is rarely conducted. Therefore, this study assessed the influence of different spectral details simulated from PRISMA hyperspectral imagery by resampling the spectral details using various spectral response function from different multispectral images such as RapidEye (4 bands), Landsat-8 OLI (8 Bands), Sentinel-2 (13 bands), and MODIS (19 bands) for detecting change classes using unsupervised approach of Principal Component Analysis (PCA) and K-means clustering [14]. The purpose of making the simulation model is to find out whether the increase in the spectral resolution of an image is directly proportional to the increase in the ability of the image to detect changes. The results from using the original hyperspectral bands were also compared in this study.

2 Methods

This study focuses on detecting changes based on spectral differences taken from multitemporal PRISMA hyperspectral images. The PRISMA image developed by the Italian Space Agency (ASI) has 237 spectral channels with a spectral resolution of 12nm. The spatial resolution of the PRISMA image is 30 m with a recording area of 30 km. In this study, bitemporal PRISMA data was used and The PRISMA image used in this study, is in the Level of 2D which has been corrected for atmospheric and has been orthorectified.

2.1 Study area

This research was conducted in parts of Boyolali and Magelang Districts, Central Java Province, where there are various types of land cover such as agricultural areas, non-agricultural areas, open land, as well as settlements and related non-agricultural lands [15, 16]. This research area has 2 land formation units, namely land formation units from volcanic processes and land formation units from structural processes, this causes the majority of the research area to be hills, slopes, valleys and have fertile soil. Based on this, the most dominant land use is agriculture and non-permanent areas such as forests. The use of land in the form of agriculture makes the research area has a fairly high change due to the relatively short agricultural harvest period. The research study area can be seen in Fig 1.

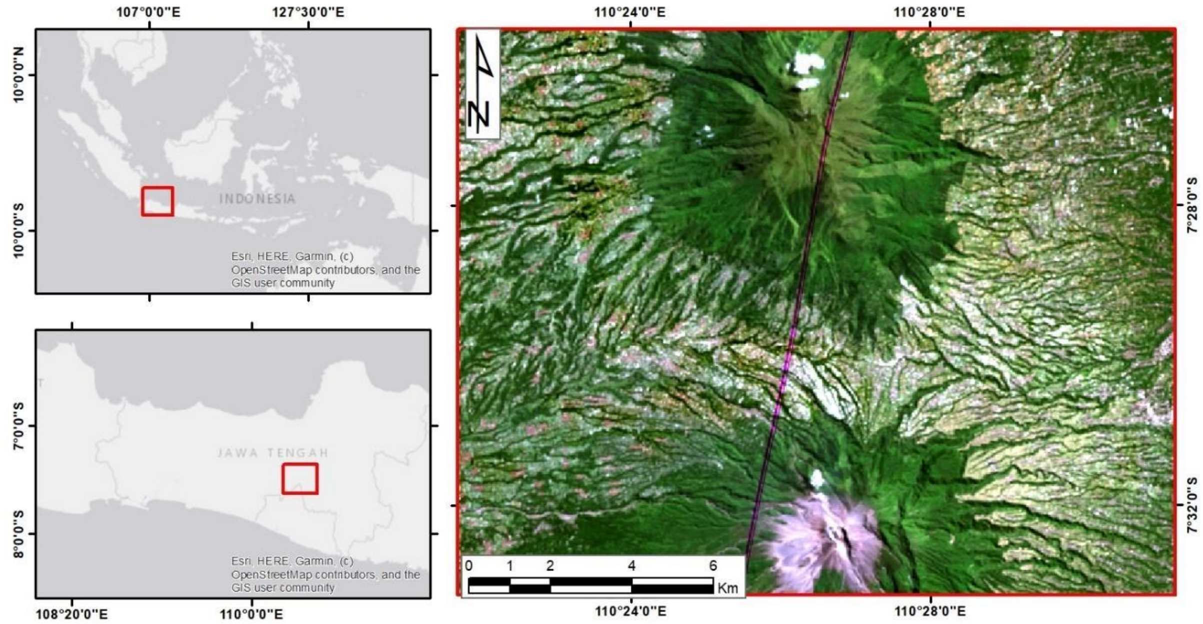

Fig. 1. Study site

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2.2 Pre-processing.

Before using the image data, the geometry correction was carried out using the image-to-image method using Arcmap software with a high spatial resolution PlanetScope as the reference image. Then the topographic correction provided by the RStoolbox Package [17] at RStudio was carried out to reduce errors caused by the topographical conditions of the research area. In this study, C-correction method was used for the topographic correction since it was considered to perform better than the other methods [18]. topographic correction requires Digital Elevation Model (DEM) data as a reference. In this study using DEM data from ALOS Palsar which is downloaded for free on Earthdata (nasa.gov). After that, to reduce interference at low and high frequencies, noise filtering is applied in the signal package [19] using the savitzky-golay method.

2.3 Spectral Resampling and Change Detection analysis.

The main purpose of this spectral resample process is to construct several levels of spectral levels by simulating them from hyperspectral data. Ready-to-use PRISMA images that have been corrected and then resampled into RapidEye (4-bands), Landsat-8 (8-bands), Sentinel-2 (13-bands), and MODIS (19-bands) using the spectral resampling function at hsdar package [20]. The application of the spectral resample method uses data centre wavelength and FWHM (Full Width Half Maximum) for each image. The results of the resample process and the original image are then performed an image difference and then the PCA method is applied to reduce interference and also reduce the dimensions of the data to avoid the "Hughes" phenomenon [21]. Then K-Means unsupervised is applied to PCA data to detect 2 binary classes of change and no-change.

2.4 Accuracy Assessment.

The results of the detection of changes at each spectral level are tested for accuracy to determine their respective capabilities. The accuracy test was carried out using PlanetScope images that has a spatial resolution of 3.7 m in the hope of representing changes in more detail and more accurately. The PlanetScope image used is one that has a time range close to the date of the PRISMA image. The accuracy test process is carried out visually by comparing the results of the change detection analysis with planetary scope image data. We use 300 sample points that are randomly distributed and then calculated using a confusion matrix for accuracy calculations.

3 Results and Discussion

3.1 Pre-processing results

PRISMA Hyperspectral data on the acquisition date April 2021 and July 2021, in parts of Central Java were used in this study. Several pre-processing methods were applied, such as image to image co-registration with a total RMS Error of less than 1 pixels, Topographic Correction and Savitzky Golay. The results of the noise filtering process using a filter length 25 can be seen in Figure 2 where the sharp changes in the frequency in the raw data become smoother and have more character. Finally, after pre-processing, the image data is ready for use with small geometric errors and has a topographic fit in the field and has low frequency interference. Spectral simulation model and dimension reduction were performed using Spectral Resample and PCA methods. Spectral Resample is used to compile simulations of various spectral levels using Center Wavelength and FWHM image information. Spectral resample is applied to each PRISMA multi-temporal Hyperspectral image and image difference is performed at each spectral level. The resample process with the image reference can be seen more clearly in Figure 3.

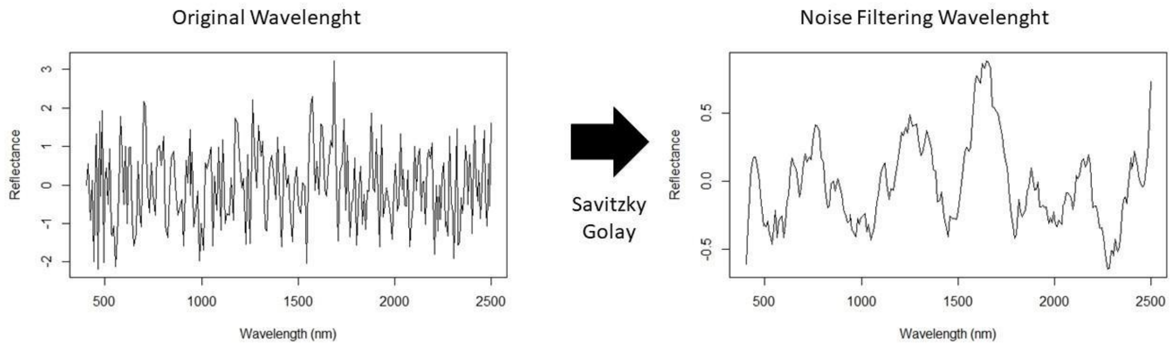

Fig. 2. Savitzky Golay Ilustration

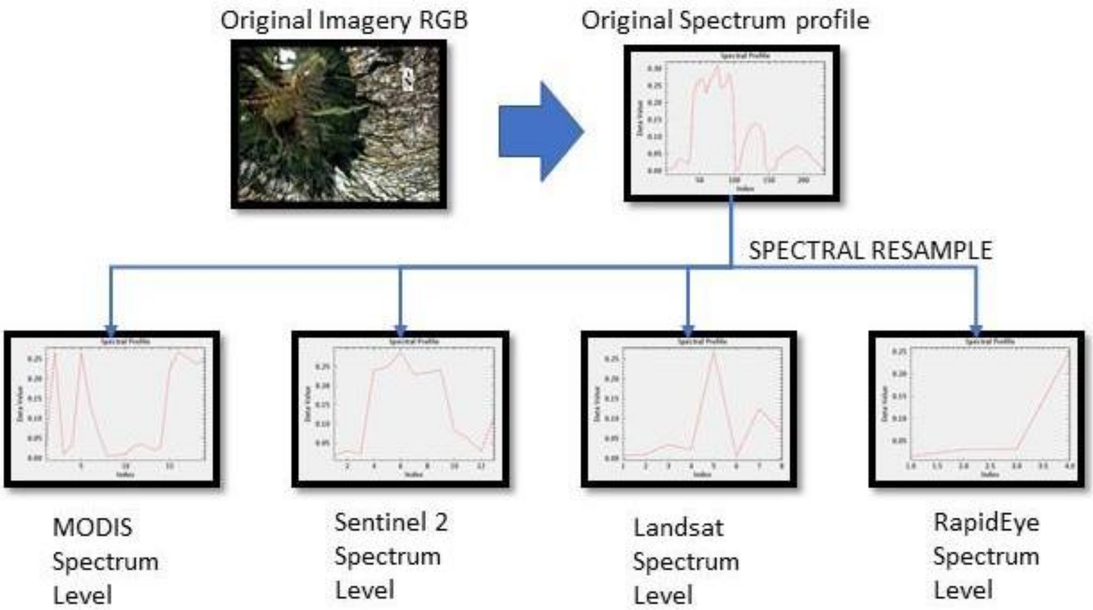

Fig. 3. Spectral Resample Scheme

3.2 Binary Change Detection and Accuracy Assessment Results

The result of image difference using each simulated data were then processed by using PCA and the results of PCA were used as the input for K-Means analysis to generate binary change classes. The results of the accuracy from each spectral level indicated the ability of each spectral level to detect change classes. The results of the accuracy test can be seen clearly in Table 1. Based on the table, it can be seen that the higher the spectral resolution does not always make the accuracy higher, where the highest overall accuracy of 72.04% is obtained by RapidEye and Sentinel 2 images. PRISMA images with 237 spectral channels are only able to obtain an accuracy of 65.74%. These results indicate that the detection of changes in land cover can be done only with 4 – 13 bands. Figure 4 shows the distribution of changing and unchanged results in the study area. A clear distribution of changes occurred in the slopes of Mount Merbabu where at the RapidEye and MODIS image levels very little change was detected and from Landsat to Sentinel 2 and PRISMA the changes detected increased. It is different with Mount Merapi where the detection of changes at the RapidEye, Landsat and MODIS levels is quite similar and at Sentinel and PRISMA are different. The spectral level of RapidEye and Sentinel 2 images which have the highest accuracy results, there is a significant difference where in Sentinel 2 the distribution of changes is dominant in the eastern area (Boyolali and its surroundings), while the resulting RapidEye changes are quite evenly distributed throughout the study area.

Table 1. Accuracy Asessment Result

Spectral Level	UA (%) (no-change class)	PA (%) (no-change class)	UA (%) (change class)	PA (%) (change class)	OA (%)
RapidEye	**86,70**	67,69	56,70	**80,29**	**72,04**
Landsat	85,71	67,44	56,70	79,14	71,54
Sentinel 2	78,82	**70,18**	**64,95**	74,56	**72,04**
MODIS	**86,70**	66,17	53,61	79,39	70,53
PRISMA	81,28	62,74	49,48	71,64	65,74

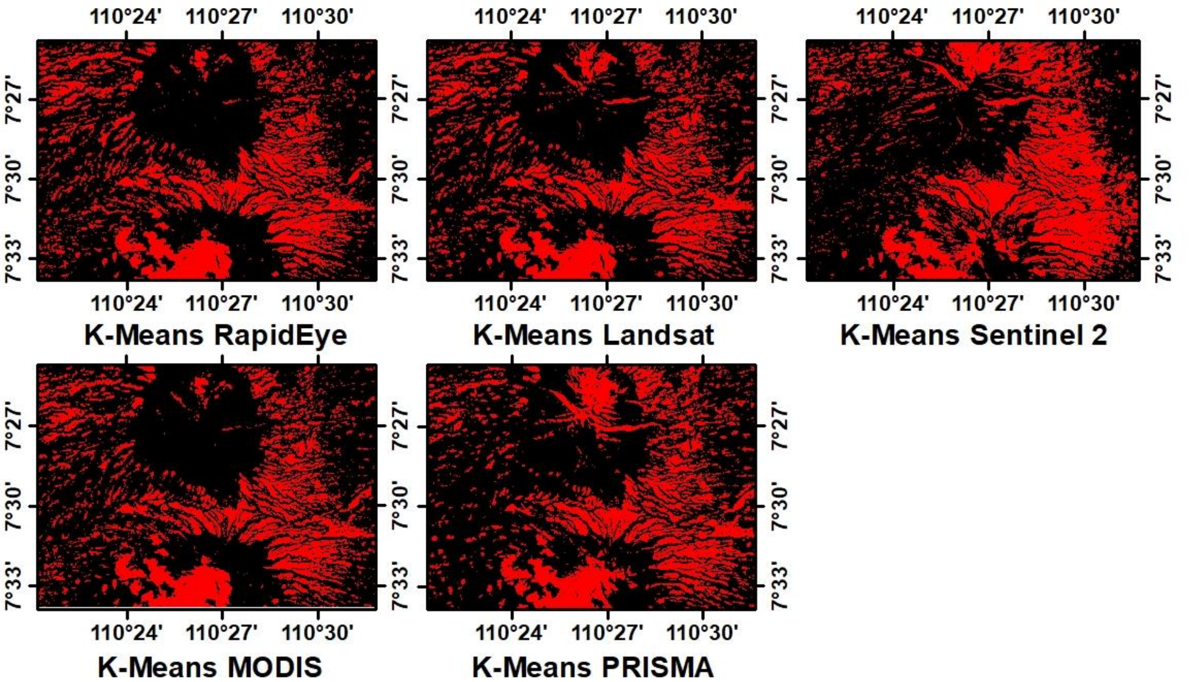

Fig. 4. Change Detection Result

Hyperspectral images with more bands produce the lowest accuracy value with a value of 65.74%. This can be caused by a relatively high noise in the hyperspectral data which not add the capability for detecting change. Odd results occur at the Sentinel and MODIS image levels. The Sentinel-2 results show the dominant distribution of changes to the east. MODIS results have the oddity of having similar results to RapidEye but having a different accuracy of 2% difference, this can be influenced by the channel combination from MODIS which is not very good for detecting changes in land cover in the study area. The MODIS spectral configuration has been designed for a coarse resolution analysis and intended for various purposes, including general land cover mapping, weather and atmospheric monitoring so that it may not fit to be used in detail change detection analysis.

The difference of the two results from using MODIS and Sentinel-2 can also be due to the quality of PRISMA image data which has poor red edge band quality, besides that the reduction in bands due to striping can also affect the overall results. The distribution of changes is generally found in the area around the mountain slopes where the area is agricultural land due to the planting season in July 2021.

4 Conclusion

This study examined the ability of various spectral levels of images that are simulated using PRISMA hyperspectral data. There are 5 results of change detection analysis generated by processing change detection at each spectral level. In general, change detection results show good accuracy results with a relatively small difference in accuracy. However, the results from Sentinel 2 have an oddity where the changes detected are dominant in the eastern area and the results from the Modis level are similar to RapidEye but have lower accuracy. MODIS spectral configuration may not fit to be used to be simulated using the hyperspectral bands since it is not intended for change detection at medium scale. The best change detection results are produced by RapidEye and Sentinel 2 images with different distributions. In addition, this study proves that the premise is that the more spectral channels, the more accurate the detection of changes is less precise because the types of changes that occur and the combination of channels have a significant effect. This showed that the discovery of significant changes in the surface cover can be produce utilizing 4 to 13 band . However, the hyperspectral data still has the potential to be studied further for detection of subtle changes in the surface cover and detection of changes based on unmixing. Furthermore, the exploration of different change detection methods may also yield a different results so that future exploration is still needed.

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References

1. S. Ghosh, S. Patra, and A. Ghosh, An unsupervised context-sensitive change detection technique based on modified self-organizing feature map neural network. *Int. J. Approx. Reason.*, **vol. 50**, pp. 37-50,(2009).
2. D. Lu, P. Mausel, E. Brondizio, and E. Moran, Change detection techniques. *Int. J. Remote Sens.*, **vol. 25**, pp. 2365-2401. (2004).
3. A. Singh, Review article digital change detection techniques using remotely-sensed data. *Int. J. Remote Sens.*, **vol. 10**, pp. 989-1003, 1989.
4. A. H. Chughtai, H. Abbasi, and R. K. Ismail, A review on change detection method and accuracy assessment for land use land cover. *Remote Sens. Appl.: Soc. Environ.*, **vol. 100482**, 2021.
5. S. Liu, D. Marinelli, L. Bruzzone, and F. Bovolo, A review of change detection in multitemporal hyperspectral images: Current techniques, applications, and challenges," *IEEE Geosci. Remote Sens. Mag.*, **vol. 7**, pp. 140-158. (2019).
6. S. T. Seydi and M. Hasanlou, A new land-cover match-based change detection for hyperspectral imagery. *Eur. J. Remote Sens.*, **vol. 50**, pp. 517-533, 2017.
7. D. Guo, W. Shi, M. Hao, and X. Zhu, FSDAF 2.0: Improving the performance of retrieving land cover changes and preserving spatial details. *Remote Sens. Environ.*, **vol. 248**, pp. 111973, (2020).
8. C. Wu, B. Du, and L. Zhang, Hyperspectral anomalous change detection based on joint sparse representation. *ISPRS J. Photogramm. Remote Sens.*, **vol. 146**, pp. 137-150, (2018).
9. M. Dalponte, L. Bruzzone, L. Vescovo, and D. Gianelle, The role of spectral resolution and classifier complexity in the analysis of hyperspectral images of forest areas. *Remote Sens. Environ.*, **vol. 113**, pp. 2345-2355. (2009).
10. S. Pignatti, A. Palombo, S. Pascucci, F. Romano, F. Santini, T. Simoniello, A. Umberto, C. Vincenzo, N. Acito, and M. Diani, The PRISMA hyperspectral mission: Science activities and opportunities for agriculture and land monitoring, in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, pp. 4558-4561. (2013)
11. E. Lopinto and C. Ananasso, The Prisma hyperspectral mission. in *Proc. 33rd EARSeL Symp. Towards Horizon*. (2020).
12. M. Kamal and S. Arjasakusuma, "Ekstraksi Informasi Penutup Lahan Menggunakan Spektrometer Lapangan Sebagai Masukan Endmember pada Data Hiperspektral Resolusi Sedang," *Jurnal Ilmiah Geomatika*, **vol. 16**. (2010).

13. M. Hasanlou and S. T. Seydi, "Hyperspectral change detection: An experimental comparative study," *Int. J. Remote Sens.*, **vol. 39**, pp. 7029-7083. (2018).
14. T. Celik, "Unsupervised change detection in satellite images using principal component analysis and k-means clustering," *IEEE Geosci. Remote Sens. Lett.*, **vol. 6**, pp. 772-776. (2009).
15. S. Arjasakusuma, P. Danoedoro, S. Herumurti, Y. A. Nugroho, and P. A. Aryaguna, "Land-Soil Characteristics For Mapping Paddy Cropping Intensity Using Decision Tree Analysis from Single Date ALI Imagery in Magelang, Central Java, Indonesia," *Geoplanning: J. Geomatics Plan.*, **vol. 4**, pp. 187-200. (2017).
16. S. Arjasakusuma, S. Kusuma, W. Mahendra, and N. Astriviany, "Mapping Paddy Field Extent and Temporal Pattern Variation in a Complex Terrain Area using Sentinel 1-Time Series Data: Case Study of Magelang District, Indonesia," *Int. J. Geoinformatics*, vol. 17, 2021.
17. B. Leutner, N. Horning, and M. B. Leutner, "Package 'RStoolbox'," *R Foundation for Statistical Computing*, Version 0.1, 2017.
18. S. Hantson and E. Chuvieco, "Evaluation of different topographic correction methods for Landsat imagery," *Int. J. Appl. Earth Obs. Geoinformation*, vol. 13, pp. 691-700, 2011.
19. U. Ligges, T. Short, P. Kienzle, S. Schnackenberg, D. Billinghurst, H.-W. Borchers, A. Carezia, P. Dupuis, J. W. Eaton, and E. Farhi, "Package 'signal'," *R Foundation for Statistical Computing*, 2015.
20. L. W. Lehnert, H. Meyer, W. A. Obermeier, B. Silva, B. Regeling, and J. Bendix, "Hyperspectral data analysis in R: The hsdar package," *arXiv preprint arXiv:1805.05090*, 2018.
21. S. Arjasakusuma, S. Swahyu Kusuma, and S. Phinn, "Evaluating variable selection and machine learning algorithms for estimating forest heights by combining lidar and hyperspectral data," *ISPRS Int. J. Geo-Inf.*, vol. 9, pp. 507, 2020.