Work Package 2.4

Part IIIA:

Land use classification over a highly-urbanized region using multi-resolution images

Abstract:

Mapping land use classes can be challenging especially in highly-urbanized regions due to the diversity of materials and structures. We aimed to generate a land use classification for Metro Manila by combining spatial data derived from Sentinel-2 image, IFSAR DEM and DSM and segmented WorldView2 images and classified land use using Support Vector Machine. We were able to generate a land use classification with an overall accuracy of 81.6%. Our results show that the addition of informational layers such as height of the structure, dimensions, texture, distance and density improved the classification accuracy by 13.8% higher than when the RGB image classification. In addition, informal settlements can be classified more accurately (PA=85.86% and UA=79.07%). There was a great difficulty in accurately classifying industrial (PA=69.06% and UA=69.32%), commercial areas (PA=66.34% and UA=73.46%) and residential areas (PA=65.92%, UA=70.52%). These results can help in estimating the informal settlement population and exposure to various hazards in Metro Manila.

We also mapped the land use for 2011 using LiDAR DEM, DSM and orthophoto for Metro Manila, Pasig City and Barangay Batasan Hills in Quezon City to apply the methodology using another dataset. Using the same methodology, but without ground truthing activity, results appeared to have overestimated the informal settlements for Metro Manila and Quezon City. The best land use classification was for Barangay Batasan Hills. Even without ground truthing and relying on visual assessment, this exercise showed that adding more spatial information layers enable land use classification. In addition, this study showed that the collection of sufficient training and ground truthing sites are important in improving the land use classification accuracy.

1. Introduction

Land use refers to the anthropogenic function of a space (Lambin, et al., 2006) including residential, commercial, industrial, agricultural, mining, recreational, institutional, and others. This information differs from land cover which refers to the biotic or abiotic material on and above the ground (Lambin, et al., 2006). The varying utilization of land cover for anthropogenic activities suggests land use (Lambin et al., 2006; Murayama, Estoque, Subasinghe, Hou & Gong, 2015). While both pieces of information are relevant, they provide insights necessary for various analyses. Land use is a critical information necessary for understanding the way we deal with our environment (Meng, Currit, Wang, & Yang, 2010), for planning and managing our urban space, and for understanding space utilization patterns (Zhou, Huang, Troy, & Cadenasso, 2009).

Remote sensing has been a common and tested tool for classifying land use and land cover (Zhou, Huang, Troy, & Cadenasso, 2009). The greater availability and quality of satellite images and the accompanying advances in remote sensing techniques propelled the growing number of land use and cover studies (Zhou, Troy, & Grove, 2008; Zhou, Huang, Troy & Cadenasso, 2009; Cablk & Minor, 2003; Goetz, et al., 2003; Lu & Weng, 2009; MacFaden, et al., 2012; Weng, 2012; Lichtblau & Oswald, 2019). Now, studies recommend the use of satellite images with less than 5-meter resolution for classifying land use and cover especially in built-up areas (Sugumaran, Zerr, & Prato, 2002; Goetz, Wright, Smith, Zinecker, & Schaub, 200; Van der Sande, de Jong , & de Roo, 2003; Xu, Gong , Seto, & Spear, 2003; Wang, Sousa, Gong, & Biging, 2004; Lu & Weng, 2009; cited in Moran, 2010). They prefer finer resolution images as it allowed analysis of pure pixels (Lu & Weng, 2009) depicting the land features in greater detail (Moran, 2010). This is helpful especially in urban areas where the surface materials have great variety over smaller distances (Van der Sande, de Jong , & de Roo, 2003; Moran, 2010 Lichtblau & Oswald, 2019).

In addition to finer resolution images, remote sensing now offers greater dimension through the advent of active satellite sensors like SAR or Synthetic Aperture Radar and LiDAR or Light Detection and Ranging. “LiDAR technology determines the distance between ground objects and sensors by measuring the time a pulse of transmitted energy takes to return to the LiDAR sensor” (Meng, Currit, & Zhao, Ground Filtering Algorithms for Airborne LiDAR Data: A Review of Critical Issues, 2010) These images are commonly used to produce topographic datasets like Digital Elevation Models (DEM) mostly for modeling hydrologic and hydraulic processes. LiDAR, in particular, provides remotely-sensed data with greater dimension that allows production of Digital Surface Model and Digital Terrain Model. Both DSM and DEM exhibited the ability to improve the accuracy of land use and cover classification as shown in the studies of Meng, Currit, Wang & Jang in 2010, Moran in 2010, Jia in 2015 and Lichtblau and Oswald in 2019. Finer resolution data and greater dimensionality of data can make the dataset too complex for the conventional techniques hence requiring development of new techniques (Meng, Currit, Wang, & Yang, 2010).

Mapping land use presents a greater challenge than land cover mapping, more so in the urban areas, because land use has to be classified based on the context of human activities therefore, requiring greater processing of information to derive the utilization from satellite images (Meng, Currit, Wang, & Yang, 2010). Multiple studies discussed the difficulties of classifying the different types of built-up use (Gong & Howarth, 1992; Herold, Liu, & Clarke, 2003; Lu & Weng, 2006; Meng, Currit, Wang & Yang, 2010).

However, fine ground resolution alone does not guarantee the accuracy of land use/cover classification. While fine resolution images revealing the necessary details of urban landscape, they also present challenges in image processing not only in the large volume of data to be processed but also on the use of traditional classifiers that are suited for medium resolution images. Fine resolution images have greater deviation in the spectral characteristics of a land cover class (Moran, 2010; Lichtblau & Oswald, 2019) making it more difficult to separate a land cover class from other classes (Yan, Shaker, & El-Ashmawy, 2015). The traditional image classification techniques require high separability among the classes to have accurate results challenging traditional techniques that classify images on the pixel level (Mesev, 2003; Lichtblau & Oswald, 2019).

Objective

The primary objective of this part of the study is to generate a land use classification over a complex highly-urbanized region, Metro Manila in the Philippines. Here, we would like to test whether the addition of spatial layers containing context information such as dimensions, texture, density and distance improves land use classification accuracy. In the conduct of this study, the use of combination of multispectral and radar data of varying resolutions in classifying urban land use types would also be tested. The land use classification results would elucidate the land use patterns in this urban landscape. This data would be helpful for land use planning, disaster risk reduction and mitigation

2. Material and Methods

2.1 Description of the study site

The study site covers Metro Manila, a highly urbanized site with complex land use pattern. Metro Manila covers an area of approximately 600 km^2. All of its cities are classified as urban and have high density. Metro Manila is the National Capital Region and the centre of economic, political, social and educational activities. It houses many of the business districts of the Philippines. Numerous political and educational institutions are also located in this region.

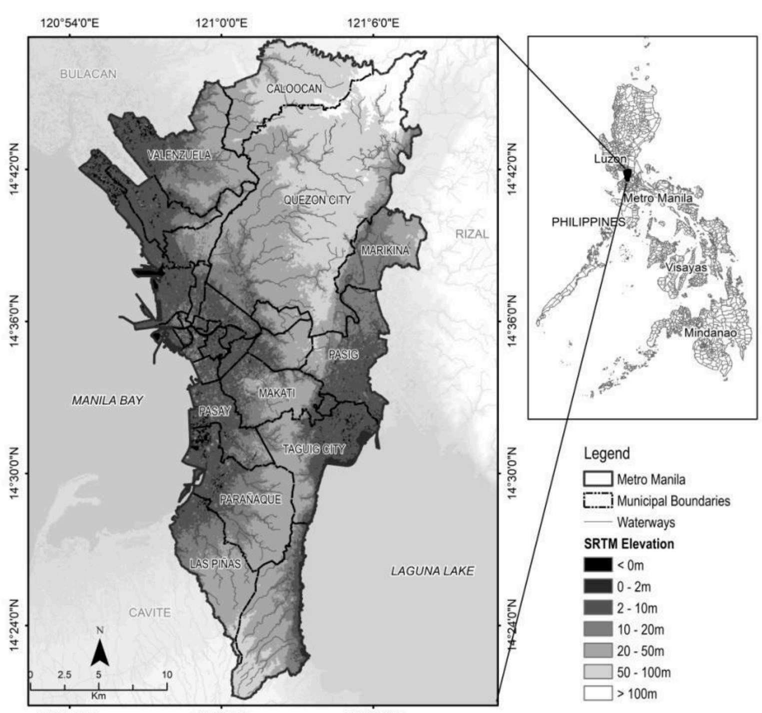

Figure 1. Location map of the study site, Metro Manila

2.2 Materials

Three different satellite data: Worldview-3, IFSAR and Sentinel-2 provided the basis for our land use classification. NAMRIA provided the 0.5-meter resolution orthoimagery of Worldview2 acquired in 2017. This image has already been orthorectified and enhanced and only the visible bands could be provided. It would be better if the other bands could be provided. Nevertheless, the fine resolution was helpful in detecting the individual features. NAMRIA also provided the Interferometric Synthetic Aperture Radar (IFSAR) data with 5-meter resolution that contains Digital Terrain Model (DTM) and Digital Surface Model (DSM) acquired in 2013. DTM was necessary in mapping the structure height which is an important parameter in classifying land use. This IFSAR data is the most recent data available. It was assumed that the difference in land use between 2017 and 2013 was minimal. As the infrared bands were not available from the Worldview-3 image, Sentinel-2 was used as a substitute.

Table 1. Input Data

Data	Year	Bands	Ground Resolution
Worldview-3	2017	Visible	0.5m
IFSAR	2013	DTM and DSM	5m
Sentinel-2	2018	Visible and NIR	10m

2.3 Methods

1. Data preparation

The input datasets were projected to a common projection, WGS 85 UTM 51N datum to ensure correspondence among images. The images were clipped to National Capital Region boundaries from NAMRIA. This was done to focus the processing on the study site and reduce processing time and file size. After clipping, the Worldview-3 and IFSAR were resized to 10 meters to reduce processing time and data volume. The requirement for the project is to classify the image for the entire Metro Manila. Reducing the resolution to 10 meters is a compromise as this would still generate enough details for the study site's scale. It was resized to 10 meters to match the ground resolution of Sentinel2 image.

Spatial information layers were processed separately. IFSAR Normalized Difference Surface Model (NDSM) was computed by subtracting the DEM from the DSM. This provided the object height information. Slope was also derived from the NDSM.

NDVI which is a common measure for vegetation health was computed using Sentinel-2 image's red and NIR bands. This would separate the vegetation from the non-vegetation land cover. Texture parameters including entropy and second angular moment were computed on the WorldView-3 image using Grey Level Co-occurrence Matrix (GLCM). Texture provides information necessary for separating the urban densities particularly the informal settlements (Kohli, Sliuzas & Stein, 2016). The co-occurrence filter size selected was 9x9 windows as it removes unnecessary artefact leading to grainy image while preserving the pattern of urban structures.

A decision tree classification was executed to separate the vegetation, elevated structures, water and ground surface based on NDVI, NDSM and MNDWI values. This decision tree classifier generates the initial classes necessary for the computation of distance and densities. Vegetation, elevated structures and ground surface were extracted from the decision tree classification image. Raster and point density for the built and vegetation classes were computed. The density information would help separate the informal and the formal residential areas. Informal settlements usually have dense building patterns while the formal residential areas have lower density of buildings and higher density of vegetation. Euclidean distance was used to compute the distance from vegetation and from the ground to better separate the industries and commercial areas from residential building. Residential buildings, especially the formal residential ones have less distance from vegetation. Commercial and industrial buildings tend to be far from vegetation. Distance from ground surface (bare soil, roads or grasslands) was also computed using Euclidean distance. Commercial areas tend to be closer to roads and grounds (i.e. parking spaces and open grounds) compared with industrial areas.

The WorldView-3 image was segmented using mean shift segmentation of RGB bands to break the image down to features or objects. This reduces the amount of data to be processed. Instead of processing pixels, the pixels are grouped as objects in vector format. Previous researchers also showed success in VHR land use classification using object-based analysis (Cai, et al., 2019; Gianinetto, et al., 2013; Ma, et al., 2017). Having a vector file also allows the computation of segment area that can add basis for land use classification. After segmentation and preparation of the indices and computation of distance and density, zonal statistics were computed for each segment. This gives a single zonal value for a segment. This removes variance for each segment and allows classification per segment. For the NDSM layer, the mean height per segment and the standard deviation per segment were computed.

2. Classification

Two sets of data were classified. The first set was plainly the RGB bands of WorldView3. The second set includes all the layers derived from WorldView3, IFSAR and Sentinel2. This set has a total of 15 bands including mainly the RGB bands of WorldView3, the decision tree classification and NDVI. It also includes layers giving information on dimension such as mean NDSM, standard deviation of NDSM and slope. Texture layers include the entropy and second angular moment. Distance from vegetation and distance from ground are also included in the stack. Lastly, built-up and vegetation kernel and segment density were also integrated to the image stack. Support Vector Machine (SVM) programmed in Envi 5.3 was used to classify the image. SVM is a robust classification technique as shown in previous studies (Jimenez, Vilchez, Gonzles, & Flores, 2018; Deilmai, Ahmad, & Zabihi, 2015). Karan & Samadder (2018) compared ML, NN, SVM, Mahalanobis, Minimum Distance, and Spectral Angle Mapper and learned that SVM produced the most accurate land cover classification for VHR image. In executing SVM, we selected the Radial Basis Function as the Kernel type with an error penalty weight of 100 and

Gamma value of 0.167 as it was superior among the tested kernel types according to the study of Yang (2011).

3. Accuracy assessment

Ground truthing activity was performed in July 8-12, 2019 traversing accessible roads while taking geotagged photos of urban structures to determine existing land use at specific points (Figure 3 to Figure 6). Land use classes were selected via a stratified random sampling. With the aid of Google Earth, almost 3,500 polygons (with an area representing 1.4% of the total area of Metro Manila) were collected around Metro Manila (see Table 2). Some of the polygons were used for classification training and the remaining points were used for ground truthing to check the accuracy of the classified image.

Table 2. Area of training sites per class

Land Use Class	Area (sq.m.)	%
Commercial	782,400.00	14.17
Bare	245,800.00	4.45
Residential	857,600.00	15.53
Informal Settlements	1,587,400.00	28.74
Industrial	1,258,700.00	22.79
Grass	200,500.00	3.63
Tree	79,500.00	1.44
Water	510,900.00	9.25
Total	**5,522,800.00**	**100.00**

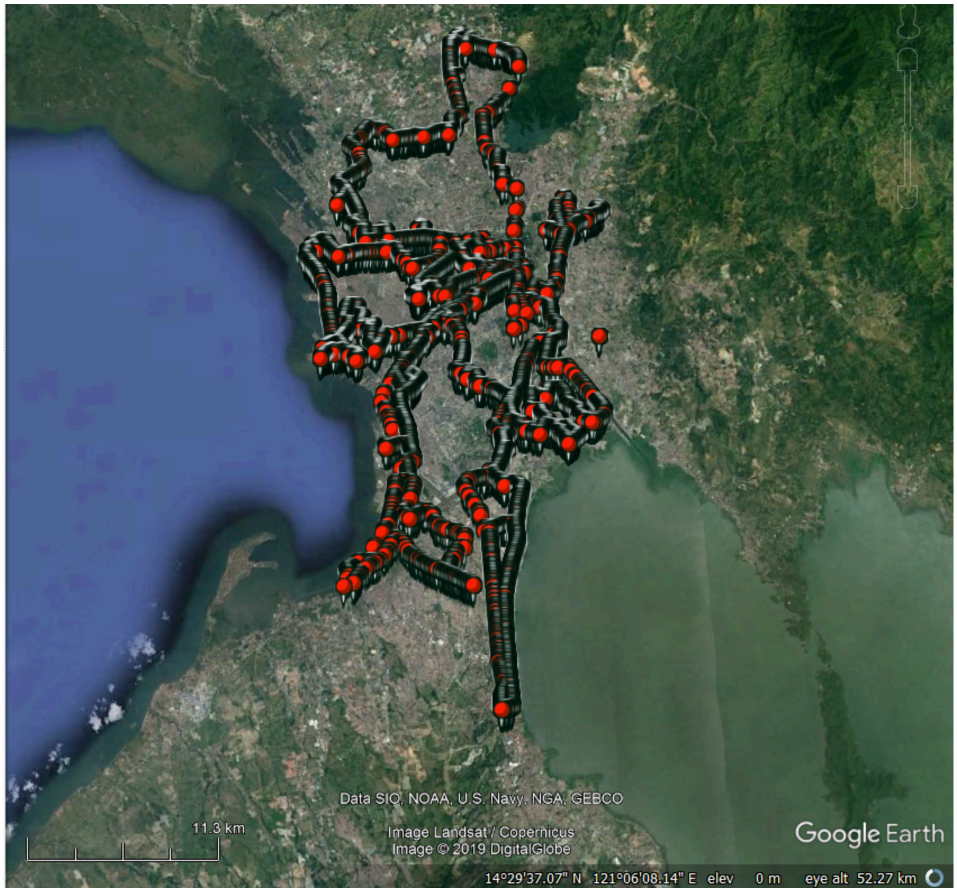

Figure 2. Ground truthing points (July 8-12, 2019)

Figure 3. Satellite image (left) and ground truth image (right) of informal settlements characterized by dense housing units without regular order among the units. Housing units are constructed of a mixture of wood, metal sheets, concrete and plastic tarpaulins.

Figure 4. Satellite image (left) and ground truth image (right) of an example of formal residential area. Formal housing has more space for parking and plants. The house structures are also made of more durable materials like concrete, wood, metal and glass.

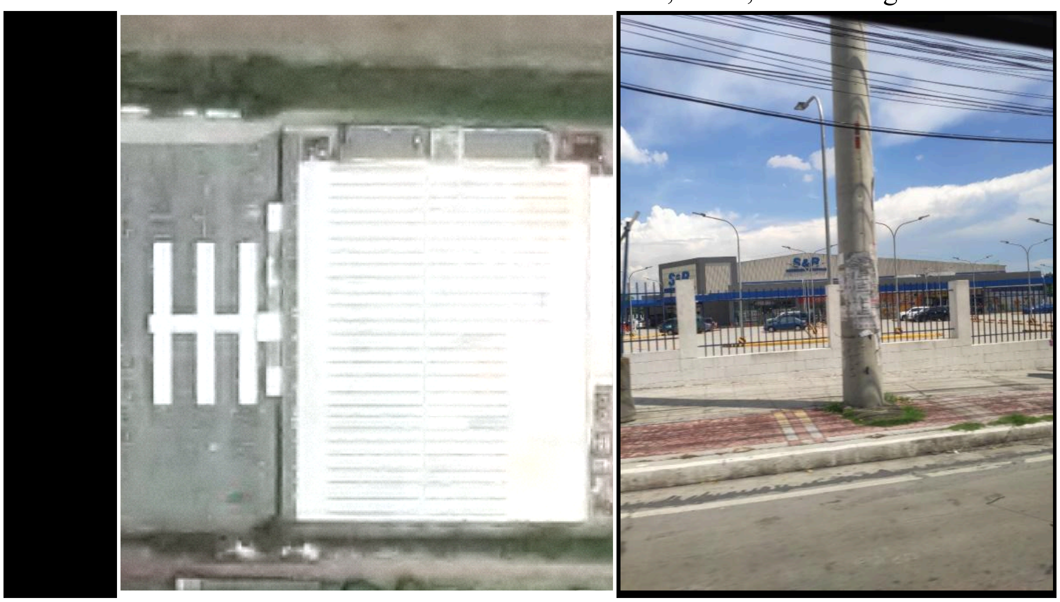

Figure 5. Satellite image (left) and ground truth image (right) of major shopping centers have parking lots and are near major roads. Major commercial buildings are located along major roads. Major commercial establishments cover large area and are often more than 3 floors high. They are built of durable materials like concrete, metal and glass.

Figure 6. Satellite image (left) and ground truth image (right) of industrial establishments cover large area as well but have tall gates in front. Inside the compound are several buildings made of concrete, metal and some glass. Some of the large manufacturing plants are along secondary roads

3. Results

Land use classification accuracy assessment

Integrating spatial information from various image sources yielded up to 13.8% more accurate classification results. Overall accuracies of SVM classification using RGB bands and using multiple images with spatial information layers of WorldView3 image were 67.8% and 81.6%, respectively. The confusion matrices shown in Table 3 and Table 4 show the breakdown of the correctly classified pixels per class for the RGB image classification (set 1) and for the image stack with the spatial information layers (set 2), respectively.

Table 3. Confusion matrix of RGB image classification (com=commercial, bare=bare soil, res=residential, IS=informal settlements, ind=industrial)

	Ground Truth (Pixels)								
Classified	Com	Bare	Res	IS	Ind	Grass	Tree	Water	Total
Com	3334	0	425	325	2070	0	0	2	6156
Bare	101	2071	261	34	302	0	0	0	2769
Res	313	1	2672	921	954	31	27	199	5118
IS	1561	196	2964	14242	2771	0	0	1	21735
Ind	1848	99	1274	273	5494	0	0	92	9080
Grass	0	39	43	1	8	1966	2	0	2059
Tree	6	0	171	7	22	8	2426	7	2647
Water	195	52	766	71	966	0	1475	11748	15273

Total	7358	2458	8576	15874	12587	2005	3930	12049	64837

Table 4. Confusion matrix of image classification with spatial layers (com=commercial, bare=bare soil, res=residential, IS=informal settlements, ind=industrial)

	Groundtruth Pixels								
Classified	Com	Bare	Res	IS	Ind	Grass	Tree	Water	Total
Com	4881	26	113	76	1546	0	0	2	6644
Bare	13	2141	4	38	55	0	0	0	2251
Res	188	0	5653	1287	860	0	25	3	8016
IS	317	11	1881	13629	1399	0	0	0	17237
Ind	1955	189	852	823	8692	2	0	26	12539
Grass	0	39	6	1	0	1994	2	0	2042
Tree	0	0	55	0	2	9	3903	8	3977
Water	4	52	12	20	33	0	0	12010	12131
Total	7358	2458	8576	15874	12587	2005	3930	12049	64837

Set 2 has higher producer and user accuracy compared with the classification using the RGB image alone. This is true for all the classes except for informal settlements class (Table 6). The PA of IS dropped from 89.72% for RGB to 85.86% for integrated layers. This means that some of the additional spatial layers caused confusion and misclassification of the IS to either residential or industrial classes. Nevertheless, the PA is still acceptable. Moreover, the PA and UA were significantly improved for the integrated layers.

The classifier had a difficulty in correctly classifying commercial and industrial area caused by the similarity of the two classes. Classification was correct for the tall commercial buildings as industrial buildings tend to be lower. Classification was also correct for the malls. The confusion mostly occurs for the smaller commercial establishments along the major roads.

The algorithm misclassified some residential area as informal settlements. Some informal settlements are transitioning to formal residential area (Figure 7, Figure 8 and Figure 10). This creates a mixture of formal and informal structures (Figure 9). Some formal residential areas are experiencing decay due to old housing structures and in turn resemble the degraded materials of informal settlements (Figure 11 and Figure 12). These factors caused confusion in the land use classification. On the satellite image, the details that can be observed from the ground suggesting the formality of the settlements are not visible. Another factor affecting the classification accuracy is the variation in the time of data acquisition. The most recent DSM and DEM data available for the study site is 2013. The VHR image provided was acquired in 2017 and the Sentinel 2 data was acquired in 2018. Within the span on 5 years, some changes may have occurred in the buildings. Some of the informal settlement housing units may have been demolished or improved.

Figure 7. Informal settlement transitioning to formal residential area

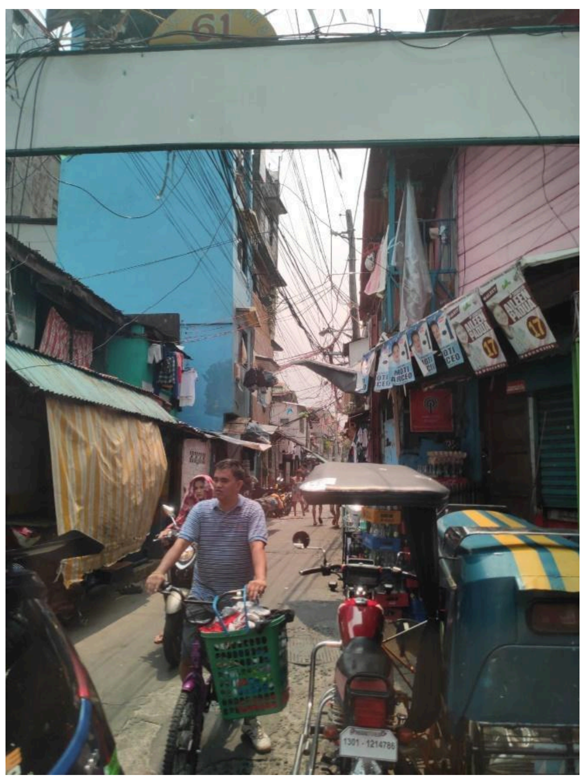

Figure 8. Dense residential area with formalizing housing units

Figure 9. Mixture of formal and informal settlements

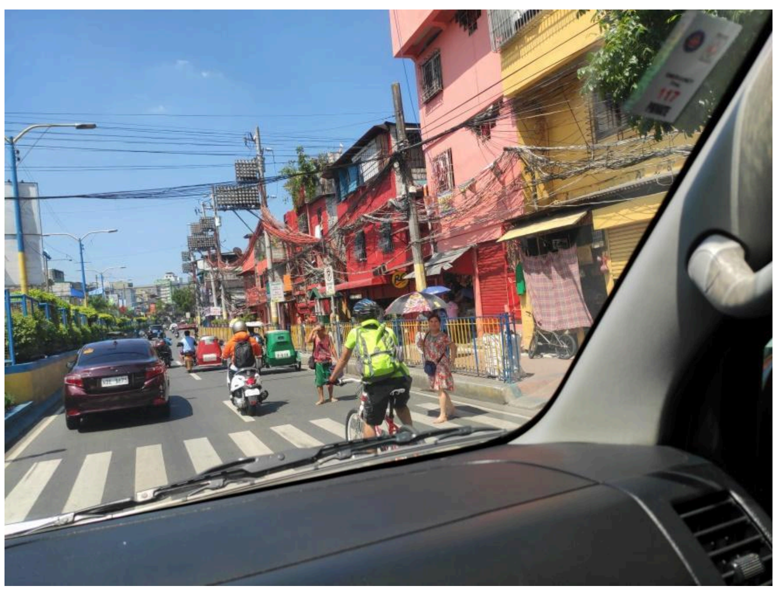

Figure 10. Informal settlement as indicated by the electric meters on the posts and orange electric cables that are beautified to look formal

Figure 11. Neglected formal building

Figure 12. Formal structure as suggested by the detailing on the roofs but somehow neglected and is now crumbling and could be confused as an informal housing unit

Table 6. Producer's and user's accuracy

Class	**RGB**		**Integrated layers**	
	PA %	UA %	PA %	UA %
Commercial	45.31	54.16	66.34	73.46
Bare Soil	84.26	74.79	87.1	95.11
Residential	31.16	52.21	65.92	70.52
Informal Settlements	89.72	65.53	85.86	79.07

Industrial	43.65	60.51	69.06	69.32
Grass	98.05	95.48	99.45	97.65
Tree	61.73	91.65	99.31	98.14
Water	97.5	76.92	99.68	99

Land use of Metro Manila

Residential areas and informal settlements cover 40.26% (239.8 sq.km.) and 20.28% (120.8 sq.km.) of Metro Manila (Table 7). The location of formal residential areas and informal settlements are mapped in Figure 13. Note that our definition of informal settlements is not based on legality of tenure but on the morphological characteristics of the housing units. Industrial areas (14.18% or 84.5 sq.km.) and trees (11.58% or 69.0 sq.km.) are the next predominant land use and cover type in Metro Manila. Grass, water and bare soil only cover 5.43%, 4.10%, and 2.60% of Metro Manila area, respectively. Commercial areas cover the smallest (1.56% or 9.3 sq.km.) land area in Metro Manila.

Table 7. Land use classification area estimate

Class	Area (Sq.km.)	Area %
Commercial	9.3	1.56
Bare Soil	15.5	2.60
Residential	239.8	40.26
Informal Settlements	120.8	20.28
Industrial	84. 5	14.18
Grass	32.3	5.43
Tree	69.0	11.58
Water	24.4	4.10
Total	**595.7**	**100.00**

Figure 13 illustrates the land use type distribution across cities of Metro Manila. Most residential areas surround the business districts and are located near the major highways. Informal settlements are clustered in Manila, south Kalookan and are seen as dense urban patches in other cities. Industries are located in clusters in some cities. They are the manufacturing plants, factories, warehouses. However, sometimes they can be confused as a commercial establishment due to their size. The commercial establishments are located along major roads. Some of the small commercial establishments especially the house-sized ones are not detected and classified in our study.

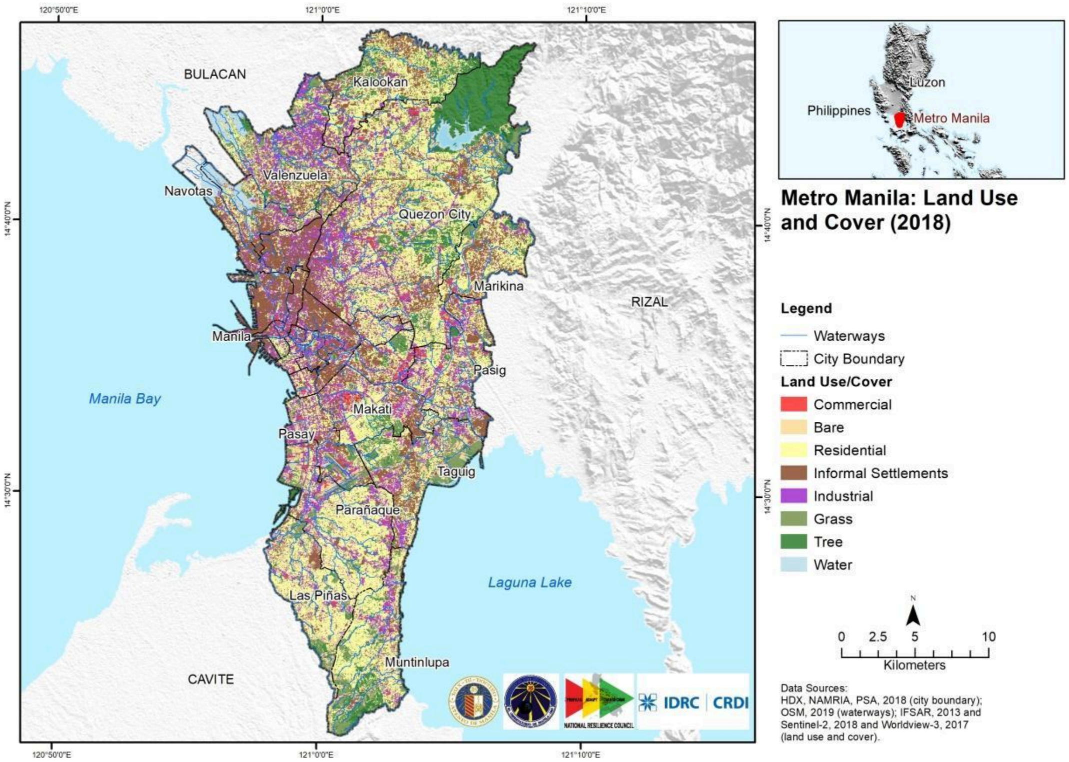

Figure 13. Land use classification of Metro Manila (Set B)

5. Conclusion

Integrating various spatial information data like dimension, texture, distance and density into the multispectral bands improved the land use classification accuracy by roughly 13% raising the overall accuracy of the classification to 81.6%. This also increased the PA and UA significantly. Overall, 60% of Metro Manila's land area is used for residential purposes (40% is formal residential and 20% is informal settlements). Industrial and commercial makes up 14% and 2%, respectively.

Recommendation for further research

Increase the number of training sites especially for industrial, commercial and residential areas to improve the PA and UA of these classes. The use of open source data for training site collection can be explored.

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Work Package 2.4

Part IIIB:

Land Use Classification of Metro Manila (2011) using LiDAR data and orthophotos

The same procedure as in the 2017 WorldView3 image was executed on the LiDAR DEM, DSM, and orthophotos taken on 2011. We also tried to add the institutional establishments in the classification scheme. However, no ground truthing activity was conducted for this image. The training sites for classification and ground truthing data used were obtained from the orthophotos and from archival data of Google Earth via visual photo interpretation. A total of 285 polygons were collected for classification training. These polygons represented roughly 0.52% of the total study site area (Table 1).

The results show difference from the land use classification results of WorldView3, Sentinel 2 and IFSAR. By visual assessment of the classification results, the classification result for Metro Manila overestimated the informal settlements. There were less formal residential areas detected and more informal settlements (Figure 1). This could be primarily caused by the number of training sites used for the classification. The total number of training sites for LiDAR classification was a third of the training data used for WorldView3 image. The informal settlement training sites were double the number of training sites for formal residential areas. This could have caused the bias in the land use classification.

Table 1. Training site area per land use class in Metro Manila

Land Use	Area (sq.m.)
Commercial	295,001.72
Informal Settlements	353,102.06
Institutional	81,900.48
Industrial	311,901.82
Residential	158,600.92
Vegetation	654,103.81
Road	172,901.01
Bare Soil	85,200.50
Water	924,805.38
Total	3,037,517.68

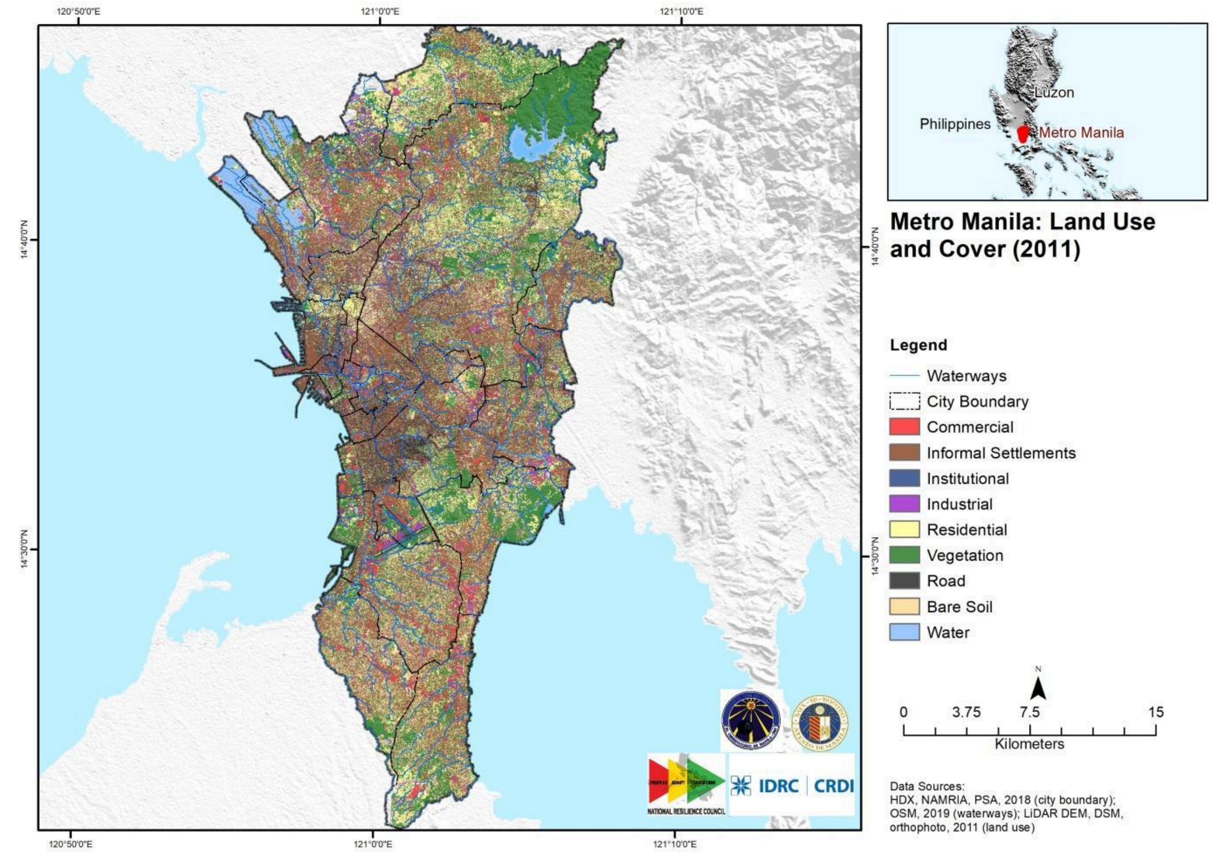

Figure 1. Land use and cover of Metro Manila in 2011

The classification method was applied to smaller coverage like Pasig City and Barangay Batasan Hills, Quezon City. The land use classification image for Pasig City also appeared to have overestimated the informal settlements. For Pasig City, the training sites collected represented 1.0% of the city's land area. For Pasig City, the ground resolution was reduced to 5 meters. At 5 meters, there are more details captured in the classification (Figure 2). Better separation between commercial and industrial areas was observed. The classified image also show resemblance with the Land Use Zoning Map of Pasig City produced in 2015.

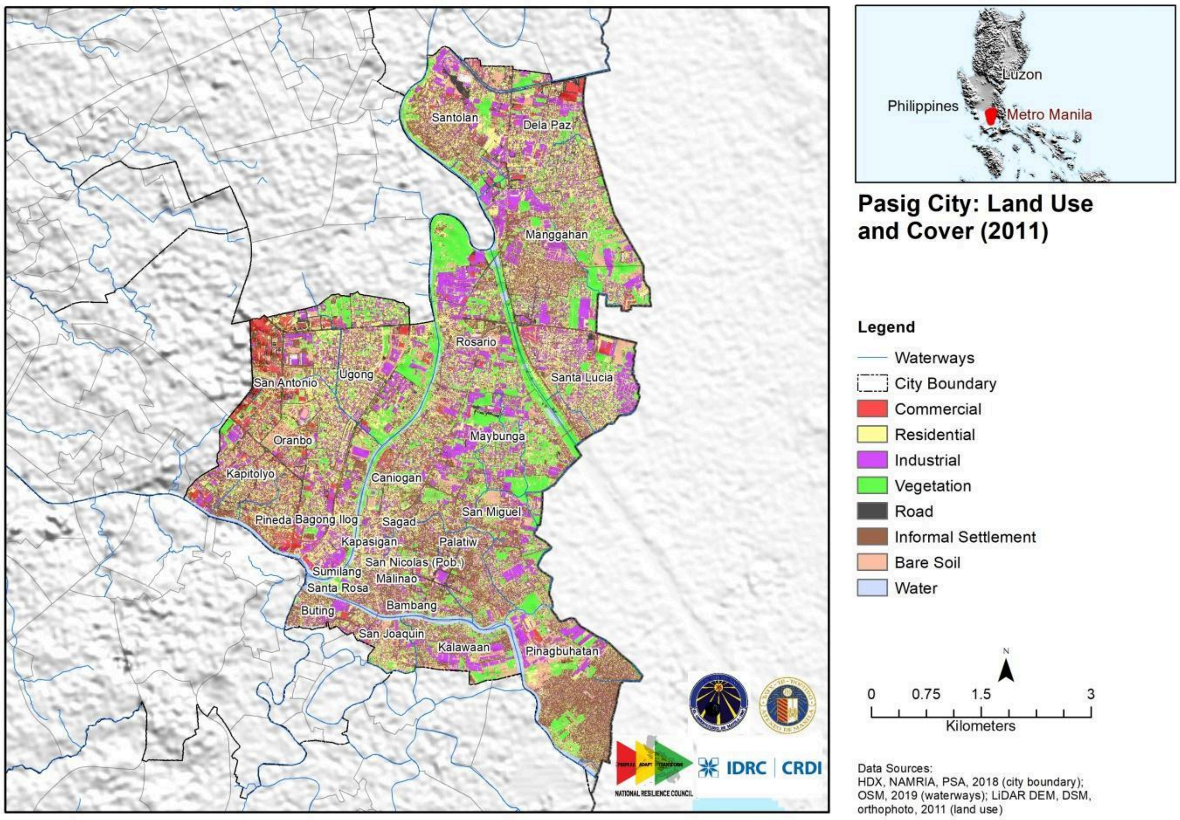

Figure 2. Land use classification of Pasig City (2011)

The classification for Barangay Batasan Hills, Quezon City appears to be the most correct classification for the LiDAR data (Figure 3). Barangay scale analysis allowed for finer resolution (2 meters) image processing. At this resolution, land use classification was able to delineate separate formal housing units and the roads. The classified image was able to correctly classify the institutional area like Batasan Complex and Sandigan Bayan. It was also able to detect a shopping center along Commonwealth Avenue. A 2-meter resolution land use classification or less would be ideal for Barangay or sub-barangay level using LiDAR data. This worked for barangay level because of more similarity within the classes. However, for regional level, there are more variation within the classes. Also, details would no longer be appreciated. It is best to perform the classification for barangay level at finer or full resolution. However, time does not permit this operation. There are more than 1,700 barangays in Metro Manila. Processing for Batasan Hills took around a week. Applying this process for 1,700 barangays would take 1,700 weeks. Also, the data storage and data processing capacity of computers would not be sufficient. Hence, the resolution had to be reduced. This reduced the accuracy and the amount of detail in the classification.

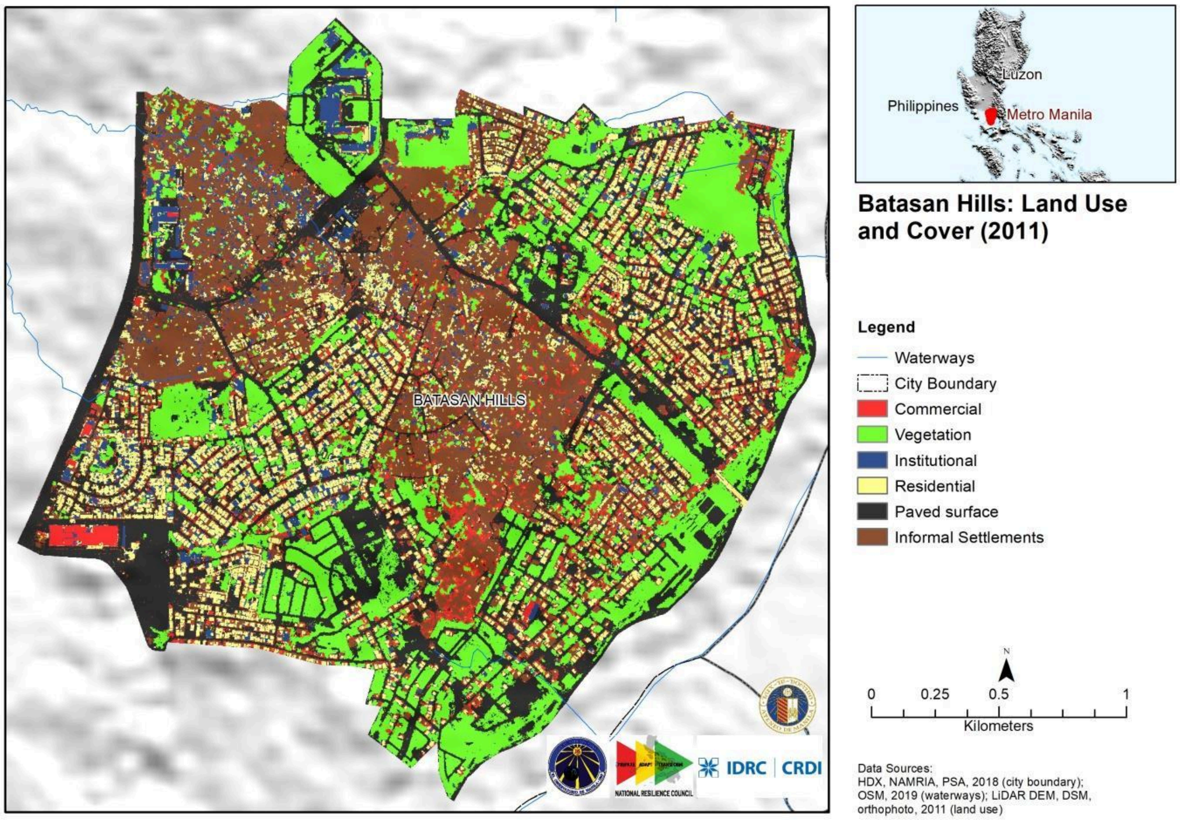

Figure 3. Land use classification of Barangay Batasan Hills, Quezon City (2011)