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Landcover Mapping Using Lidar Data and Aerial Image and Soil Fertility Degradation Assessment for Rice Production Area in Quezon, Nueva Ecija, Philippines

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Abstract**—**Land-cover maps were important for many scientific, ecological and land management purposes and during the last decades, rapid decrease of soil fertility was observed to be due to land use practices such as rice cultivation. High-precision land-cover maps are not yet available in the area which is important in an economy management. To assure accurate mapping of land cover to provide information, remote sensing is a very suitable tool to carry out this task and automatic land use and cover detection. The study did not only provide high precision land cover maps but it also provides estimates of rice production area that had undergone chemical degradation due to fertility decline. Land-cover were delineated and classified into pre-defined classes to achieve proper detection features. After generation of Land-cover map, of high intensity of rice cultivation, soil fertility degradation assessment in rice production area due to fertility decline was created to assess the impact of soils used in agricultural production. Using Simple spatial analysis functions and ArcGIS, the Land-cover map of Municipality of Quezon in Nueva Ecija, Philippines was overlaid to the fertility decline maps from Land Degradation Assessment Philippines- Bureau of Soils and Water Management (LADA-Philippines-BSWM) to determine the area of rice crops that were most likely where nitrogen, phosphorus, zinc and sulfur deficiencies were induced by high dosage of urea and imbalance N:P fertilization. The result found out that 80.00 % of fallow and 99.81% of rice production area has high soil fertility decline.

Keywords**—**Aerial image, land-cover, LiDAR, soil fertility degradation.

I. Introduction

LAND cover analysis is gaining attention globally as one of the most fundamental information systems for human activities and natural environment management. The information system mostly depends on remote sensing technology due to its ability to acquire measurements of land surfaces at various spatial and temporal scales.

With the invent of remote sensing and Geographical Information System (GIS) techniques, land cover mapping has given a useful and detailed way to improve the selection of areas designed to agricultural, urban and/or industrial areas of a region [1]. The advent of high spatial resolution satellite imagery and more advanced image processing and GIS technologies has resulted in a switch to more routine and consistent monitoring and modeling of land use/land cover patterns. Remote-sensing has been widely used in updating land cover maps and land cover mapping and has become one of the most important applications of remote sensing [2]. Remote sensing algorithm such as Object Based Image Analysis using Support Vector Machine (SVM) allows the incorporation of different properties such as spectral, geometric, and textural properties for image classification [3]. The decline in land quality caused by human activities has been a major global issue since the 20th century and will remain high on the international agenda in the 21st century [4]. The inappropriate land use can cause degradation of soil, water and vegetative cover and loss of both soil and vegetative biological diversity, affecting ecosystem structure and functions [5]-[7]. Land degradation encompasses the whole environment but includes individual factors concerning soils, water resources (surface, ground), forests (woodlands), grasslands (rangelands), croplands (rainfed, irrigated) and biodiversity (animals, vegetative cover, soil) [8]. Thus, type of vegetation must be seriously taken into account when relating soil nutrient status with environmental conditions [9], [10]. Land cover change and population dynamics are central in understanding soil fertility dynamics. It is hypothesized that the amount and distribution of a wide array of soil nutrients may vary among land-uses and landscape positions. In this study mapping of land use/cover of one of the municipalities of Nueva Ecija was conducted in view to detect the soil fertility degradation of the municipality. It is, therefore, important to understand the status and dynamics of soil nutrients in relation to land-use and landscape position.

II. Objectives

The objective of the study was to generate land-cover classification map and soil fertility degradation assessment for rice production area in Quezon, Nueva Ecija, Philippines using LiDAR Data.

III. Data and Study Area

The available datasets used in the study were aerial images and LiDAR flight strips given by the Phil-Lidar1, Data Acquisition

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Component. The LiDAR flights are PAM3H acquired last April, 28, 2014, PAM3I acquired last July 11, 2013 and Pam3J acquired last June 20, 2013. The selected study site was an agricultural area (Quezon: 15° 34' 42.355" N, 120° 49' 33.170" E) in Nueva Ecija, Philippines (Fig. 1) with surface area of 76.29 km^2. The vegetation of the area consisted mainly of rice and also large area of fallow which is intended for vegetables and rice production. Other land use of the site were residential areas and various non-crop trees.

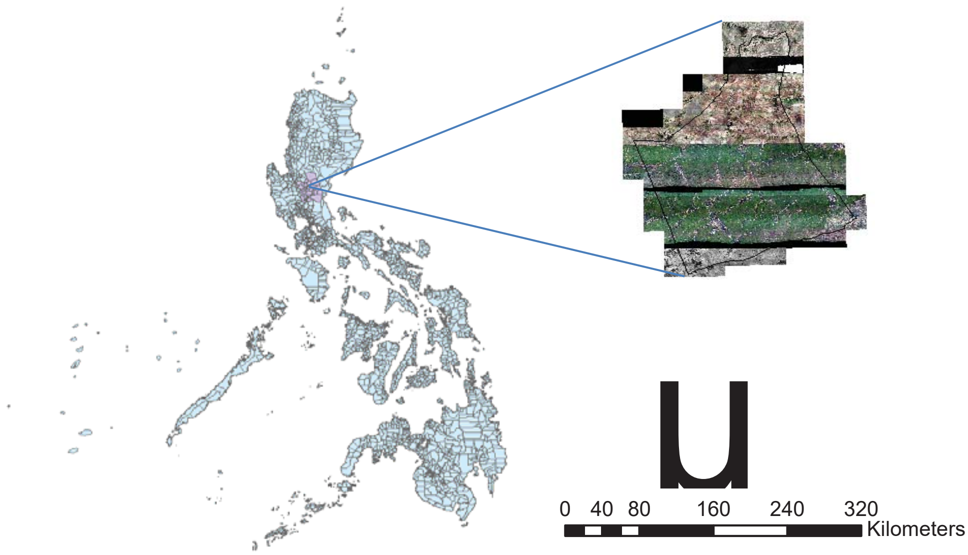


Fig. 1 Aerial image of the study site

IV. Methods

Generation of Derivatives**:** Several LiDAR derivatives were generated using Lastools, average intensity and number of returns using Lasgrid (Lastools software), while height information such as Digital Surface Model (DSM) and Digital Terrain Model (DTM) were derived using Blast2DEM (Lastools software), these height information were used to generate normalized Digital Surface Model (nDSM). A 0.5-meter resolution of ortho-image RGB bands and LiDAR data were used. HSV (Hue, Saturation and Value) was derived by transforming the original RGB bands to HSV color space. GRVI (Green Red Vegetation Index) was also derived using the Ortho-image using band math equation, using (1) [11]. Fig. 2 shows different derivatives used to generate land cover classification map:

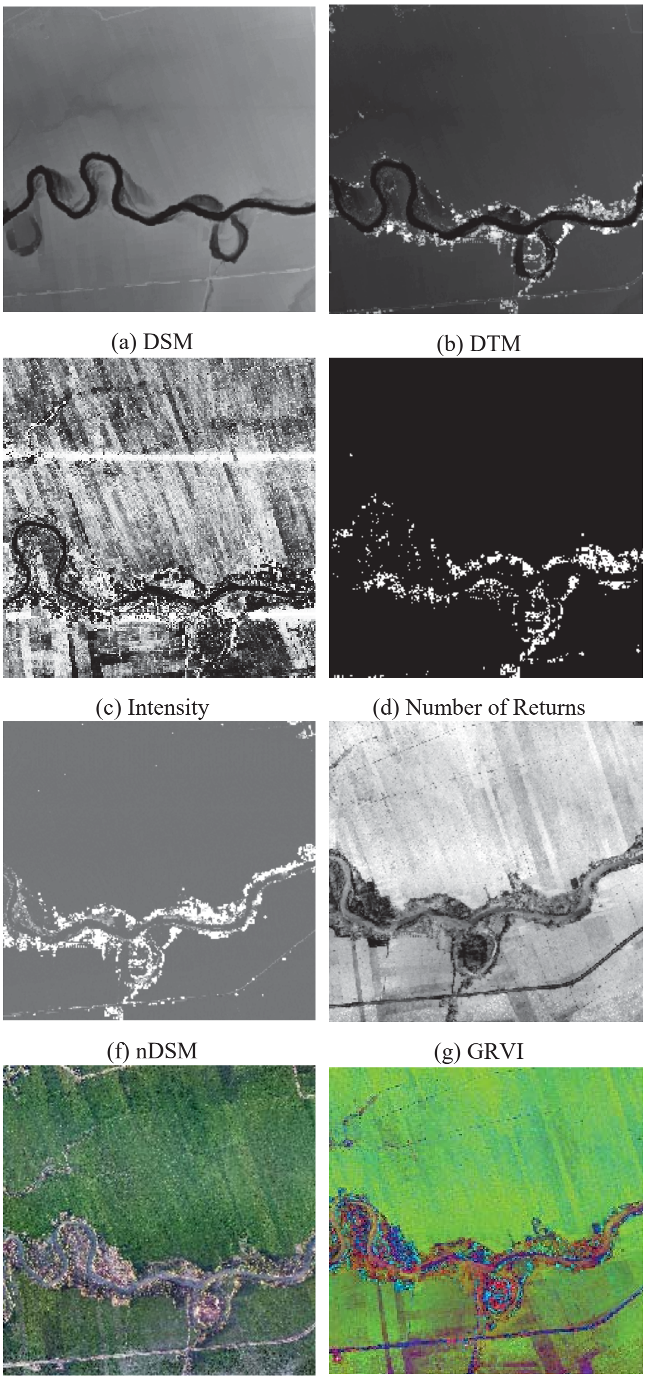
$$\text{GRVI} = \frac{\text{Green}-\text{Red}}{\text{Green}+\text{Red}} \tag{1}$$

Segmentation method: Creating representative image objects with image segmentation algorithm is important pre-requisite for classification/feature extraction [12]. The rationale of this procedure is to generate image objects that closely mirror meaningful features on the earth's surface [13]. Chessboard segmentation was first employed to segment the road, building and water using thematic layers. Multi-Threshold Segmentation was used to separate ground such as rice and fallow lands and non-ground feature such as trees, separation was done by creating larger scale for ground features and smaller scale for non-ground features [11]. Multiresolution segmentation (MRS) was used for the segmentation of pixels into image objects. The MRS uses an optimization routine that minimizes the average heterogeneity of image objects and maximizes their respective homogeneity for a given resolution.

The image layer weights for all the three bands- Blue, Green, Red and nDSM derivatives were assigned the same weight. In addition, equal weights were also given to the remaining images derivatives to extracts a set of meaningful objects. Settings for the composition of homogeneity criterion were assigned as 0.3 for Shape and 0.5 for Compactness. These parameters were found suitable to delineate vegetation and bare ground.

Support vector machine (SVM) classification: The determination of classification scheme depends on the study area and available remote sensing data [14]. The support vector machine (SVM) is a group of theoretically superior machine learning algorithms which was found competitive with the best available machine learning algorithms in classifying high-dimensional data sets [11], [15]. Multiresolution segmentation step was employed to ground and non-ground to create object prior to classification. Afterwards, features are stored in an array to facilitate easy implementation of the classification. In this study Support Vector Machine (SVM) classification of LiDAR data and orthophoto has been applied by using Radial Basis Function kernel type in eCognition software (C parameter = 200) [11]. In order to reduce the heterogeneity problem, different methods, such as use of texture in classification and object-oriented classifiers have been examined [11], [16]. Therefore different textural features based on the Grey Level Co-occurrence Matrix (GLCM) were used for the SVM classification [11]. Table I shows the list of features used for SVM Classifications. The proposed methodology is shown in

Fig. 3.



(a) DSM (b) DTM (c) Intensity (d) Number of Returns (f) nDSM (g) GRVI (g) RGB (h) HSV

Fig. 2 Different derivatives used to generate land cover classification map (a) DSM, (b) DTM, (c) Intensity, (d) Number of Returns, (e) GRVI, (f) nDSM, (g) RGB and (h) HSV

Sample Points Selection. Training data selection is one of the major factors determining to what degree the classification rules can be generalized to unseen samples [17]. A previous study showed that this factor could be more important for obtaining accurate classifications than the selection of classification algorithms [18]. Proper selection of training sample plots is critical for land cover classification [19]. Training points is important as it identifies the characteristics of the different classes. Training and validation points for different classes were selected homogeneously from the orthophoto so that only the properties unique to each class was used in separating them from one another.

TABLE I
LIST OF FEATURES USED FOR SVM CLASSIFICATIONS

Spectral Features	**Image Layers**
Mean	Orthophoto RGB
Standard Deviation	HSV transformed Orthophoto RGB
	Green Red Vegetation index (GRVI)
	Highest First Return in Lidar Intensity
	Intensity
	nDSM
Textural Features	**Image layers**
GLCM Homogeneity	Orthophoto RGB
GLCM 2nd Angle Moment	HSV transformed Orthophoto RGB
	Green Red Vegetation index (GRVI)
	Highest First Return in Lidar Intensity
	Intensity
	nDSM
GLDV Entropy	Intensity & nDSM

Field validation was done to obtain the ground true features of the municipality and to determine the accuracy of the generated map. Fig. 4 shows the sample validation points used in validating the different land cover class of Quezon, Nueva Ecija, Philippines.

Accuracy Assessment: After the classification, accuracy assessment was performed to quantitatively determine if classes have been assigned correctly. A TTA (Test and Train Area) Mask was used to compute for some statistical measures of accuracy in eCognition

Soil Fertility Degradation Assessment: The extracted Land-Cover-land-use Classification Map was exported into shapefile and loaded to ArcGIS and overlaid using fertility decline map of the Philippines to determine the high soil fertility decline areas.

V. RESULTS AND DISCUSSION

A. Land-Cover Classification Map of Quezon, Nueva Ecija

Fig. 5 shows the generated Land-Cover-Land-Use Classification Map (Agricultural Map) of Quezon, Nueva Ecija. The Municipality comprised of 10 landcover classes namely; Bare, Fallow, Built up, Calamansi, Crops/vegetables, Mango, Non-Agricultural Trees, Rice, Road and Water. The accuracy assessment indicates high levels of accuracy with an overall accuracy of 93.2%. This is higher than the recommended accuracy of 85% above which classification is considered reliable.

The results show that most of the land cover areas of Quezon are rice and wide area of fallow was identified which is also intended to rice production during rainy season. Visually, overall performance of SVM in land cover classification is good as it can classify all pixels effectively.

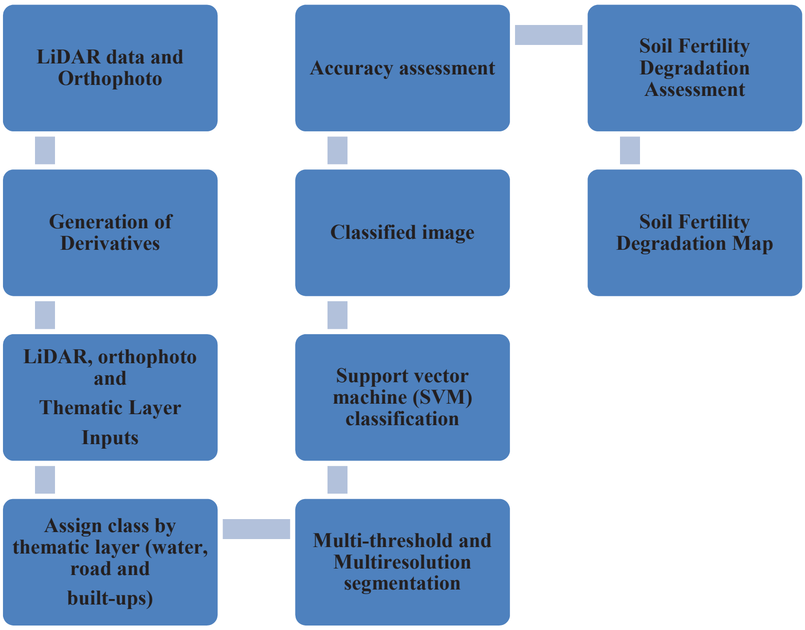


Fig. 3 Flow chart of the study

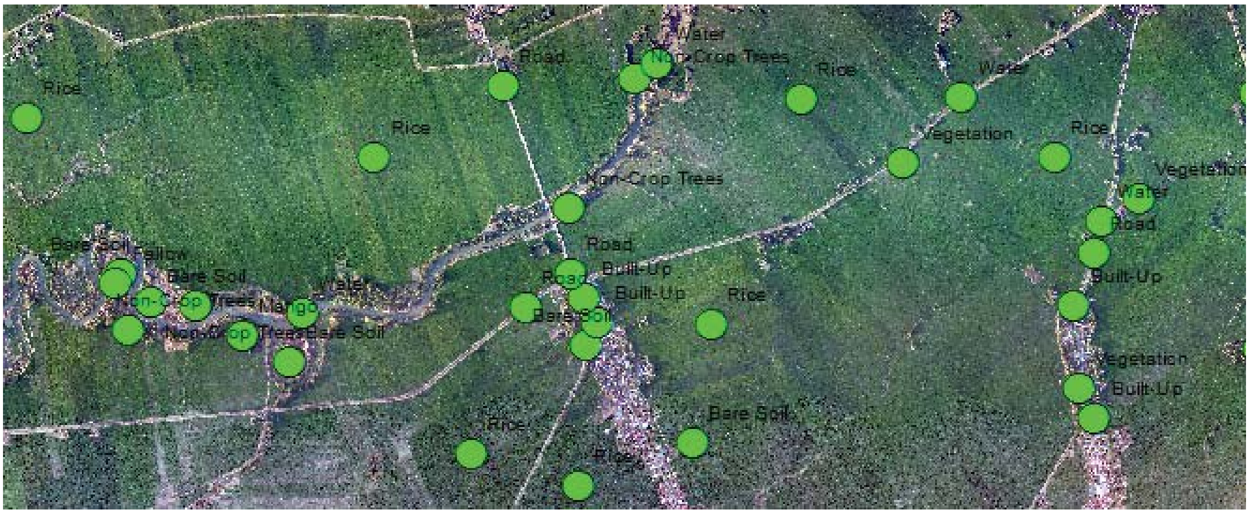


Fig. 4 The sample validation points used in validating different land cover class of Quezon, Nueva Ecija, Philippines

B. Soil Fertility Degradation Assessment

Fig. 6 shows the Soil Fertility Degradation map of Quezon, Nueva Ecija, Philippines. Results shows that 80.00 % of bare/fallow and 99.81% of rice production area has high soil fertility decline. These areas of rice crop were most likely where nitrogen, phosphorus, zinc and sulfur deficiencies were induced by high dosage of urea and imbalance N:P fertilization.

Under such situation, soil mining of nutrient elements other than nitrogen, such as the trace elements mai nly caused by the crop's (rice and corn) ability to extract higher quantity of these elements far higher than the crop needs.

This particular process has led further not only to nutrient depletion, but also to nutrient imbalances, which can be summarily known as soil chemical degradation affecting the overall soil productivity [20]. This is particularly the case in nitrogen (Urea)-driven intensive rice monoculture, which is evident in old irrigation systems in the country [20].

VI. Conclusions

The study demonstrated the applicability of object-based image classification using SVM in land-cover-land-use mapping. The techniques implemented in this study shows that accurate land-cover-land use mapping can rapidly be achieved using high resolution multispectral aerial image and object-based image classification. The use of the SVM method expedited the optimum classification of land covers. This study concluded that SVM classification has potential to rapidly improve the classification of rural areas and update rural land cover classifications. Also, the combination of simple spatial analysis and object based image analysis is suited in determining the soil fertility degradation assessment of certain municipalities.

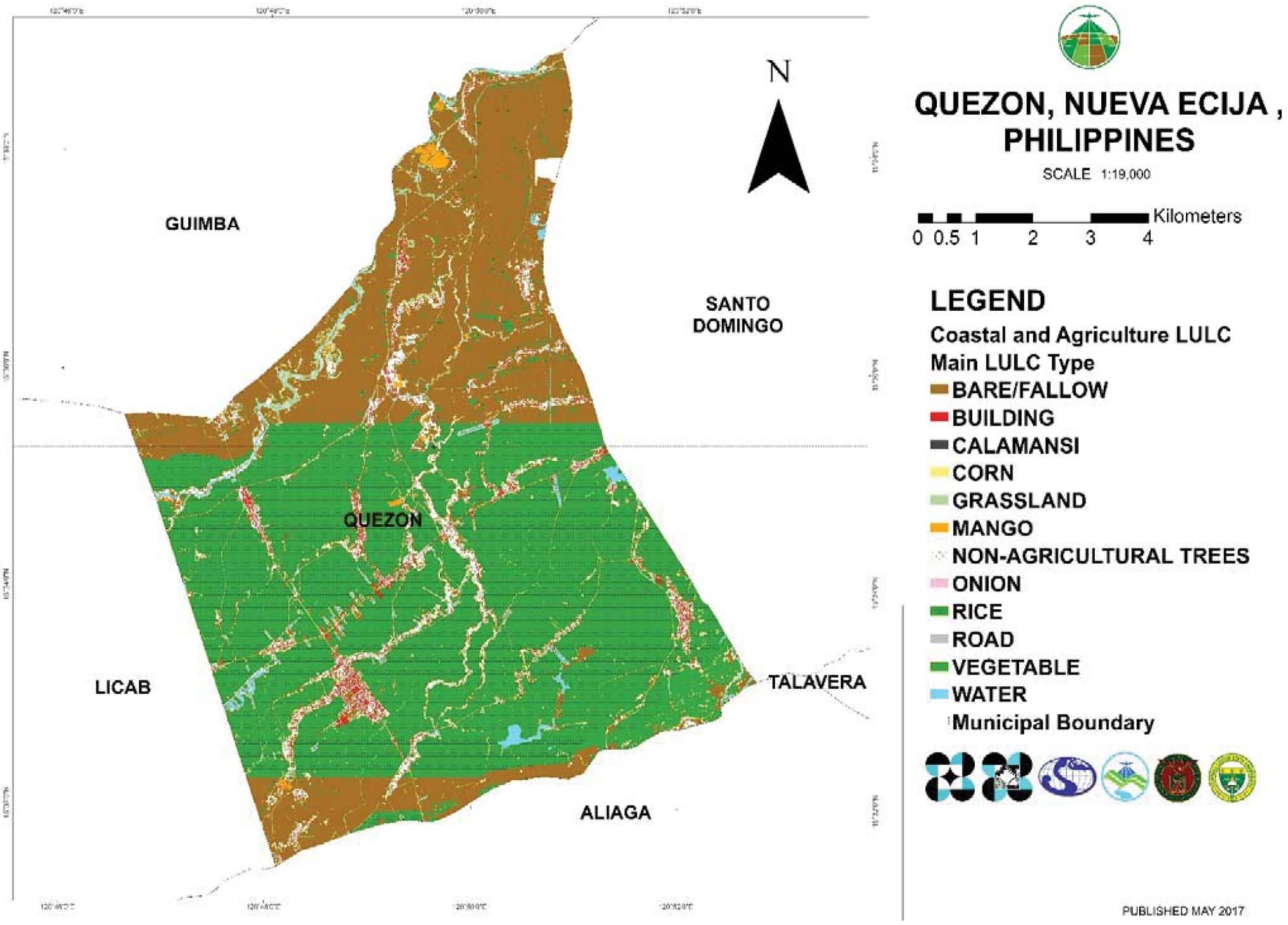


Fig. 5 Land-Cover-Land-Use Classification Map (Agricultural Map) of Quezon, Nueva Ecija, Philippines

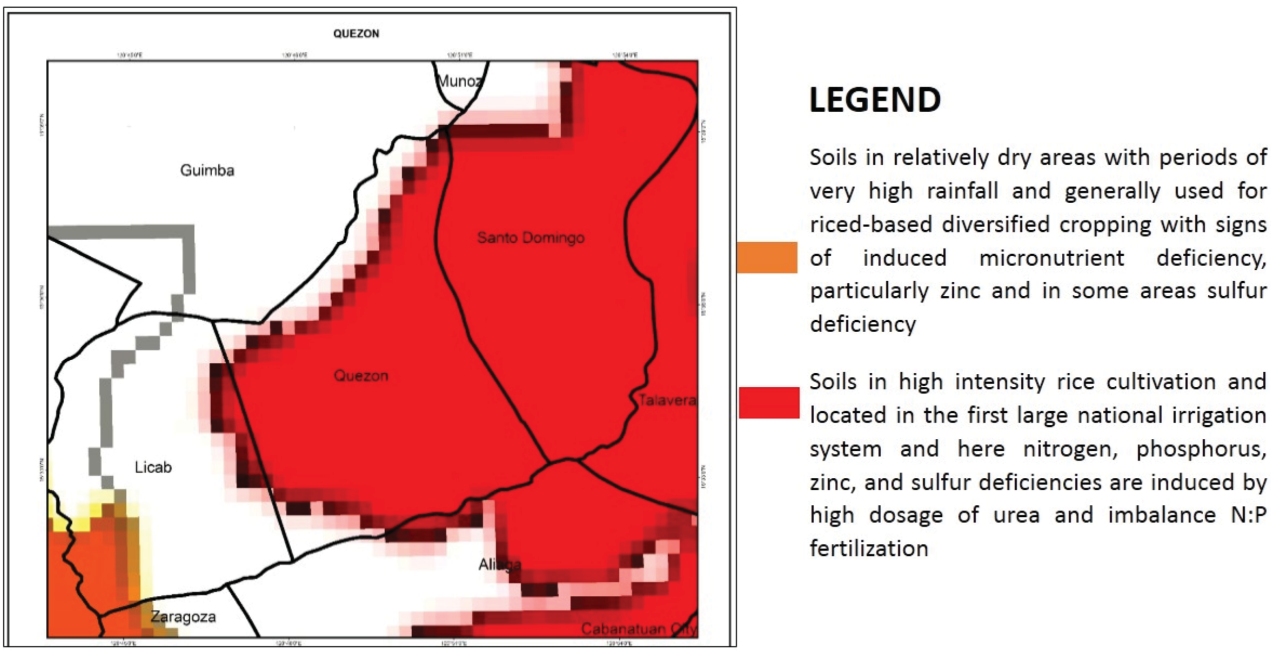


Fig. 6 Soil Fertility Degradation Map of Quezon, Nueva Ecija, Philippines

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