Forestland Rehabilitation Impact Indicators and Spatiotemporal Visualization

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Abstract— A keynote from the United Nations (UN) during the International Day of Forests, 2019, stated that a country's economic growth and social development is impacted by how rich and wide forests are growing in that place. Forests plays a significant role in the livelihood of many people and forest rehabilitation is said to be one of the best solutions to sustain the livelihood of people. Deforestation is one of the Global Forests issues that concerns the United Nations (UN) for several decades. This paper addresses the factors and predictors that affects the forestland rehabilitation significantly. And with the aid of spatiotemporal visualization, rehabilitated forestlands were easily identified and species of seedlings and trees can easily be located. For the National Greening Program of the country, the result of this paper may serve as their basis as to which factors should be considered when rehabilitation of the forestland is concerned.

Keywords— Forestland Rehabilitation, Impact Predictors, Spatiotemporal Visualization, National Greening Program.

I. INTRODUCTION

Rationale. The Sustainable Development Goals (SDG) boosted by the United Nations which is "Life on Land" promotes and emphasizes the importance and role of forests worldwide which leads to a vision to increase and inflate global forests by 2030, to 120 million hectares which is similar to the size of South Africa, was discussed during the UN Forum on Forests on January 20, 2017 along with 197 Member States including Philippines (United Nations Strategic Plan, 2017) Forests plays a significant role in the livelihood of many people; it eliminates hunger and helps alleviate poverty through the crops, fruits and raw materials that are converted into finished products. Forests are important sources of clean air and water, and are crucial as breeding place and vital habitats for biodiversity and millions of species all over the world. And forests also serve as protection and buffer from natural disasters such flood and erosions, and are crucial for combating climate change. However, for several years, United Nations have been concerned with Global Forests Issues. Deforestation is a global issue for several decades according to UN and thus it leads to a vision to increase the forestland to 120 million hectares (same size as South Africa) by 2030, along with 197 member states including Philippines. The Philippines' response to this concern was initiated collaboratively by the Department of Environment and Natural Resources (DENR) along with the establishment of National Greening Program under DENR Memorandum Circular (DMC) No. 2011-01 which has been expanded through the Executive Order (EO) No. 193 s. 2015 known as "The Expanded National Greening Program", propagates the agenda and vision to plant 1.5 billion of seedlings covering 7.1 million hectares of unproductive, denuded and degraded forestlands all over the country which is in support to government priority program to reduce poverty, sustain food supplies, protect biodiversity, and improve climate change mitigation and implementation from year 2016 to 2028. The National Greening Program had already rehabilitated 1.66 million hectares of denuded and degraded forest areas and had planted 1.37 billion seedlings for agroforestry. And yet, it still needs to cover 5.44 million hectares until 2028. That is why the government extended NGP and so called the Expanded National Greening Program. Thus, the motivation of the researcher to identify the impact factor or predictors that contributed a lot or significantly to the rehabilitation of the forestland in the country and use some visualization tool to showcase the rehabilitated part or area of the forestland.

Spatiotemporal Data. One way to form data on forests is through Geographical Information System or GIS. Earth observation and GPS satellites produces massive data sets with better spatial and temporal resolution obtained from spatiotemporal observations which are associated to spatial locations, and GIS is an efficient way to deal with these data in the form of geometry types such as point and polygon to represent locations (Ferreira, Oliveira, Miguel, Monteiro, & Almeida, 2016). Since forests changes its form and states over time, some data relating to forests are in the form of Spatiotemporal Data. Spatiotemporal data are data that relate to both space and time, and describe a phenomenon in a certain location and time or spatial fields evolving in time. The use of spatiotemporal data may be seen in biology, medicine, meteorology, transportation, ecology and forestry (Amini Parsa, Yavari, & Nejadi, 2016; and Lindstrom, Szpiro, Sampson, Bergen, & Sheppard, 2013). Spatiotemporal Visualization. In order to make use of such data sets, which are typically available in terms of sampled points and to make them visually readable, spatiotemporal visualization has been developed. A significant advantage of spatiotemporal visualization is that it provides a global view of activities or progress, from which evolutions and overall tendencies can be detected (Kuzniar & Zajac, 2015). Consequently, with the utilization of spatiotemporal data, forest changes and deforestation trends can be estimated as with the case in the Island of Tanzania and it was found out in the research of Kukkonen and Käyhkö conducted on 2014 that there was already an alarming rate and threat in the eco-system in the East-African landscape (Kukkonen & Käyhkö, 2014). König et al., 2019, also conducted a research using spatiotemporal data approach in the monitoring of biodiversity. All the species data were summarized and established through the Global Biodiversity Information Facility database including the location where these species can be found. With the said database, spatial distribution of the species where identified per region which led them identify loss of biodiversity and imbalances in the environment (König et al., 2019). Moreover, Yu et al., in their research in 2018, established that visualizations is important means of communicating and representing massive data sets. Spatiotemporal visualization sometimes in a form of shapefile can be widely used as an instrument to depict results for decision-making processes. Spatiotemporal visualization may be applied in transportation and traffic simulations, land cover change, land use and land scape simulation, flood management or spreading of diseases. "The situation of today's environmental issues and the need for sustainable development increase the importance of spatiotemporal visualization, which transforms dynamic modelling of multidimensional data into visual representations and consequently makes such data more accessible to experts as well as non-expert users", they added.

Objectives. This paper intends to present the factors and predictors that significantly affect the rehabilitation activity of the National Greening Program and to showcase the increase in size with the use of Spatiotemporal Visualization. With these objectives, the provinces' forestland increase in terms of rehabilitation may easily be identified as well as the species and/or seedlings planted mostly in every province. This paper can be a guide or can serve as a basis as to which factor should be considered when a certain forestland needs to be rehabilitated.

II. SEMANTIC ANALYSIS

Factors and Predictors. The projects done by the National Greening Program for seven years from 2011 to 2018 provided enough data that were analyzed using WEKA. The records provided consists of the following data: Region, District, PENRO, Barangay, Municipality, Province, Area, Name of Organization, Type of Organization, Component, Commodity, Species, Year, Zone, Tenure, Remarks, Area Code, Species Replanted, Category, Unique ID, Longitude, and Latitude. And with the use of WEKA Select Attributes and Ranker methods, predictors were ranked based on their significant contributions on the size of the rehabilitated forestland. Predictors were ranked as follows: Number of Projects, Number of Households, Number of Municipality, Budget Allocated, Number of Planted, Number of Barangays, and Number of Seedlings as shown in Fig 1.

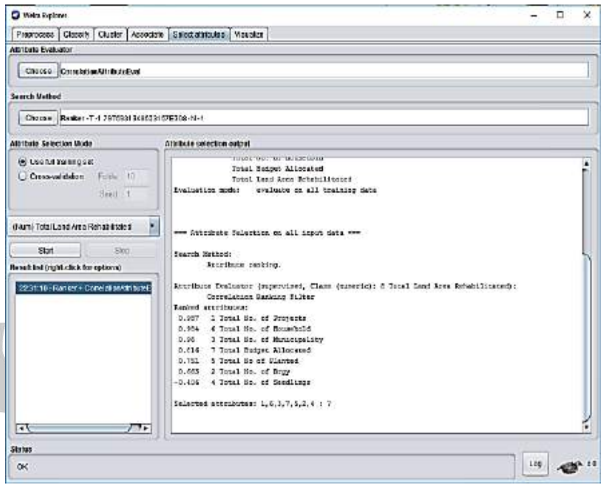

Fig 1. WEKA Select Attributes and Ranker Methods

After which, WEKA Classifier – Multilayer Perceptron was applied to generate Neural Network Single-Hidden Layer with corresponding sigmoid nodes as illustrated in Fig 2.

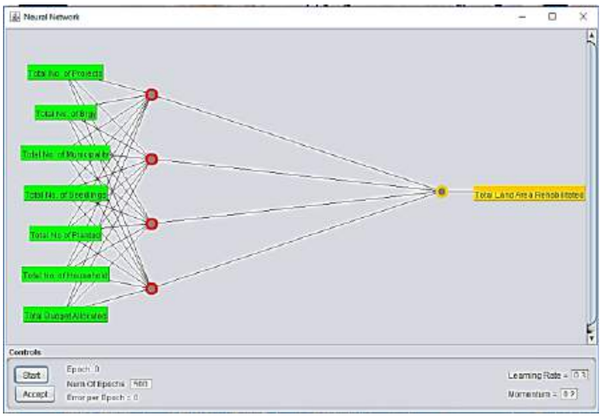

Fig 2. Multilayer Perceptron with Single-Hidden Layer for Forestland Rehabilitation

As shown in the generated diagram shown in Fig 2, to forecast the possible Total Land Area Rehabilitated, a single-hidden layer with four sigmoid nodes were formed. The diagram formed and provided by WEKA with sigmoid weights and threshold values consisting of seven predictors were ranked based on their significance and or weights.

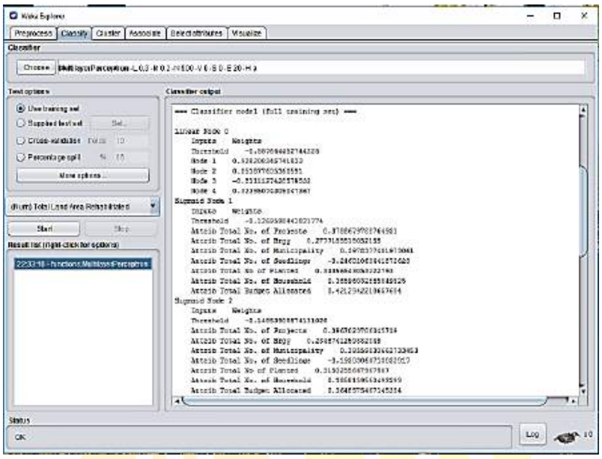

Fig 3. Sigmoid weights and threshold values

Fig 3 shows the sigmoid nodes weights and threshold which can be utilized in the computation to forecast possible increase in the size of the rehabilitated forestland. Table 1 shows the corresponding weights of the nodes and sigmoids generated from the multilayer perceptron method of WEKA. The computational technique (ANN) on which these weights were applied are shown on the Results section

Table 1. Nodes and Corresponding Weights

Inputs	**Weights**
Threshold	-0.557664452744228
Node 1	0.928208345741833
Node 2	0.851877605360591
Node 3	-0.8111127428579532
Node 4	0.32395074305047367

III. EMPIRICAL EVALUATION

A. Predictors and Their Corresponding Weights. The following tables present the predictors with their corresponding weights on every sigmoid generated by the multilayer perceptron of the neural network in WEKA.

Table 2. Predictors and Corresponding Weights on Sigmoid Nodes

Inputs	**Sigmoid Node1 Weights**	**Sigmoid Node2 Weights**	**Sigmoid Node3 Weights**	**Sigmoid Node4 Weights**
Threshold	-0.127	-0.149	-0.127	-0.127
No. of Projects	0.379	0.397	0.379	0.379
No. of Brgy	0.278	0.235	0.278	0.278
No. of Municipality	0.398	0.396	0.398	0.398
No. of Seedlings	-0.246	-0.194	-0.246	-0.246
No of Planted	0.344	0.315	0.344	0.344
No. of Household	0.386	0.386	0.386	0.386
Budget Allocated	0.421	0.365	0.421	0.421

Seemingly, Tables 2 consistently shows that the highest weight or the predictors that contributes greatly to the increase in the size of the rehabilitated forestland based on historical data are Total Budget Allocated, Total No. of Municipality, Total Number of Projects, Total Number of Household and Total No. of Planted. And the Total No. of Seedlings consistently has negative impact on all the sigmoid node since that attribute represents the number of seedlings produced but not have been planted yet.

And they were rank in this order based on their weights: Budget Allocated, No. of Municipalities, No. of Household, No. of Projects, No. of Planted Seedlings. Nevertheless, the No. of Seedlings produced got negative weights due to the reason that it does not contribute greatly to the increase in the size of the rehabilitated forestland as long as they would not be planted and therefore the No. of Planted Seedlings got a higher positive weight.

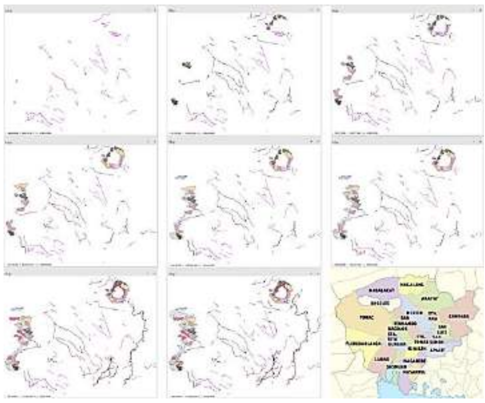

Fig 4. Spatiotemporal Visualization of the Rehabilitated Forestland from 2011 to 2018 including the flat map of the province of Pampanga indicating the municipalities

Deriving from the spatiotemporal visualization on Fig 4 Porac, Floridablanca and Arayat have the biggest or highest contribution in rehabilitating the forestland in

Pampanga. Figure 4 also showed that Porac have rehabilitated 2961.9 ha of forestland in eight (8) years, followed by Floridablanca with 1938.42 ha, Arayat with 1853.4 ha, Magalang with 685.4 ha, and Macabebe with 638.08 ha. These municipalities contributed significantly in the increase in size of the total rehabilitated area in the whole province of Pampanga from years 2013 to 2018. Apparently, having a bigger land area does not mean the municipality could contribute a bigger size of rehabilitated forestland as with the case of the municipalities of Candaba, Lubao and Mabalacat based on the result shown in the map of Pampanga in Fig 4. Candaba with land area of 18,711 ha had only rehabilitated 133 ha, Lubao with 15,731.11 ha land area have rehabilitated 44.7 ha and Mabalacat which has 8,318 ha land area has not contributed anything yet in the rehabilitation program of the NGP.

IV. CONCLUSION AND DISCUSSIONS

Determining the increase in the size of the rehabilitated forestland can be recorded using latitude and longitude, however, it will be easier to be determined and understood with the use of Spatiotemporal Visualization. Moreover, the concerned agency particularly the National Greening Program could easily identify as well as to which predictors and factors should be prioritized when planning and conducting a rehabilitation activity. With the use of WEKA, it was found out through the collated data for 7 years, that the most significant predictors were Budget Allocated, No. of Municipalities, No. of Household, No. of Projects, No. of Planted Seedlings. It was observed that the No. of Seedlings Produced had a negative weight. This means that it doesn't give much significance in the increase in the size of the rehabilitated forestland if they weren't planted. That is why the No. of Planted Seedlings carried out a positive higher weight on its sigmoid nodes and was included as one of the significant factors that contributes to the increase in the size of the rehabilitated forestland. More so, the Spatiotemporal Visualization provided a clearer illustration and visualization on the progress of the National Greening Program in terms of rehabilitating forestland. It presents the municipalities in the provinces and shows in the map where the forestland can be located and spotted.

Moreover, the species planted in every municipalities can easily be identified and known. With this feature, people who are looking for this kind of specie for economic and business purposes may find it easy to locate.

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