TEST Engineering & Management

January-February 2020
ISSN: 0193-4120 Page No. 4241 - 4250

Artificial Neural Network (ANN) with Back-Propagation Algorithm Forecasting Model and Spatiotemporal Visualization for Forestland Rehabilitation

Jehan D. Bulanadi[1], Dr. Gilbert M. Tumibay[2] and Dr. Mary Ann F. Quioc[3]
[1] IT Instructor, College of Information and Communications Technology, Holy Angel University, Angeles City, Philippines
jbulanadi@hau.edu.ph
[2] Program Chair, DIT Program, Graduate School, Angeles University Foundation
Angeles City, Philippines
tumibay.gibo@auf.edu.ph
[3] Computer Studies Professor, Mabalacat City College
Mabalacat City, Pampanga, Philippines
maryannquioc@gmail.com

Article Info
Volume 82
Page Number: 4241 - 4250
Publication Issue:
January-February 2020

Article History
Article Received: *18 May 2019*
Revised: *14 July 2019*
Accepted: *22 December 2019*
Publication: *21 January 2020*

Abstract:
For several years, United Nations have been concerned with Global Forests Issues. One of its Sustainable Development Goals focuses on Life on Land emphasizes the importance of forests to people which leads to a vision of increasing the forestland area by 2030. The Philippines, in response to this through the National Greening Program under the Department of Environment and Natural Resources is targeting to rehabilitate 7.1 million hectares of identified unproductive, denuded and degraded forestlands and need to plant 1.5 billion seedlings. This study aims to develop a forecasting model for forestland rehabilitation using Artificial Neural Network with Back-Propagation algorithm. The model will be able to identify among which of the factors or predictors contributed greatly or significantly to the changes occurred in the forestland. Results are then presented using Spatiotemporal Visualization, which illustrates the changes happened in the forestland in a yearly basis using historical data. The model may be used to forecast the size of the forestland that will be rehabilitated for the succeeding years based on the identified predictors, which may be used as a guide by the NGP for reforestation strategic planning and resource management

Keywords*—Artificial Neural Network, Back-Propagation Algorithm, Forestland Rehabilitation, Spatiotemporal Visualization*

I. INTRODUCTION

Big Data and Data Mining. Technology nowadays is without a doubt continuously advancing and evolving. Human activities may it be simple or complicated done at home, at work, in school, or anywhere people go creates volumes of data; things, moving or not also contribute and produce vast amount of data; aquatic, aerial and terrestrial plants and animals also generate data. Data come in various forms and from numerous sources, different fields and disciplines. As the technology and lifestyle improves so as the rising and increasing in volume and speed of data which forms and create Big Data [1],[2],[3]

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 [4],[5]. 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 [6],[7].

January-February 2020
ISSN: 0193-4120 Page No. 4241 - 4250

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 [8]. 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 [9]. [10] 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. Moreover [11], established that visualization 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.

Artificial Neural Network (ANN). To achieve meaningful interpretation and transformation of data particularly Forestry Big Data, data analytics techniques and algorithms, and processing tools should be carefully taken into consideration. [8] emphasized in their paper that the success of neural networks lies significantly on the form of pre-processing method applied. As an alternative method in processing and representing unpredictable data and modeling nonlinear and complex phenomena in Forestry and Environment, [12] acknowledged the findings of [13] that Artificial Neural Network or ANN is good at non-linearity processing approach. Peng, C. and Wen, X. also mentioned that ANN can provide optimal solutions to forest management problems through its predictive capability based on supervised learning and training of the system. Moreover, in the research of Imada, ANN was applied to predict forest wildfire or risk of fire occurrence in the forest based on air temperature, humidity, wind speed and rain using Multilayer Perceptron. [8],[12],[13].

II. BACKGROUND: GLOBAL AND LOCAL CONCERNS

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; 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 as flood and erosions, and are crucial for combating climate change [14],[15].

Moreover, one of 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 [14].

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. As reported by Food and Agriculture of the United Nations (FAO) during the International Day of Forests on March 2019, world population will climb to 8.5 billion by 2030 and forests will be the most and important constituent in sustaining the lives of these people [16],[17]. A study said that one mature tree can support 2 humans for their oxygen intake yearly. And it takes 10-15 years or even 20-30 years to grow and have a mature tree. There will be scarcity of clean air and oxygen as the population continues to grow and inflate every year and as trees are continuously being cut down.

Nevertheless, 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.

With regards to this, the study is anchored to one of the objectives of the National Greening Program EO Nos. 23 and 26 s. 2011, stipulated in the “Department of Environment and Natural Resources (DENR) Memorandum Circular – DMC No. 2011-01, which is to “Promote public awareness as well as instill social and environmental consciousness of the value of forests and watersheds”. With this, the researcher seeks to develop and formulate "Spatiotemporal Visualization and Forecasting Model for Forestland Rehabilitation".

And as of 2016, 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 develop a forecasting model for forestland rehabilitation.

III. Objectives

The study focuses on the application of Artificial Neural Network (ANN) with back-propagation algorithm to develop a forecasting model for the forestland rehabilitation through the use of the data extracted from the shapefiles of the NGP. Thus, this study aims to: a. process the shapefiles and extract essential data for the analysis and development of a forecasting model; b. determine the predictors that significantly affects the size of the rehabilitated forestland; c. develop a model to forecast additional rehabilitated forestland area using Artificial Neural Network with back-propagation algorithm; and d. present the data using spatiotemporal visualization.

IV. Materials And Method

Identifying how the data were collected and what composes the shapefiles determines which approach to be adopted in this study. With the underlying nature and characteristics of data and established objectives, Descriptive Research Design was implemented. Particularly to achieve the main objective of this study which is to analyze data and transform into spatiotemporal visualization, data provided by the NGP in the form of shapefiles need to be processed in a form suitable to be fed in a computational technique particularly Artificial Neural Network or ANN. Descriptive study will be implemented since it establishes associations between variables which in this case the NGP Shapefiles, Forecasting Model and Spatiotemporal Visualization for Forestland Rehabilitation

A. Conceptual Framework

Figure 1 inspired from [18], illustrates the process from input to spatiotemporal visualization and forecasting model. The NGP in every Provincial Environment and Natural Resources (PENRO) partners with community-based organization who do the rehabilitation and reforestation activities. Sites are identified for possible seedling production and plantation and corresponding seedlings or species of plants and trees are provided to the organization to plant them. Data such as the location, measurement of land area to be planted, latitude and longitude, species, and number of households, number of seedlings produced and number of seedlings planted are recorded through Geotagging which creates or produces the spatiotemporal data of NGP. From the Geotagged photos, shapefiles containing .shp, .shx and .dbf were pre-processed using WEKA to identify the factors and predictors that significantly affects the size of rehabilitated forestland. After which, a computational technique which is the Artificial Neural Network (ANN) was applied with feed-forward and back-propagation algorithm to create a model and forecast possible increase of rehabilitated forestland on the succeeding years based from historical data of NGP.

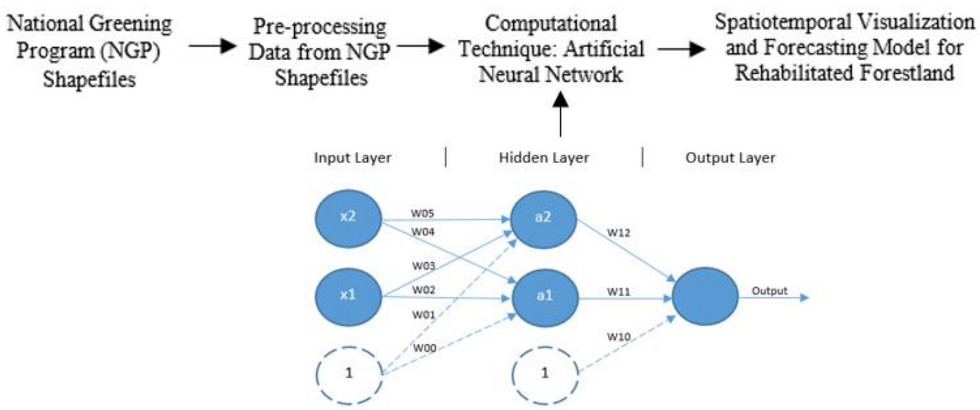


Fig 1. Artificial Neural Network (ANN) with Back-Propagation Algorithm and Spatiotemporal Visualization for Forestland Rehabilitation

A. Specific Procedures

Data cleaning, Pre-processing and Application of WEKA

Data were provided by the National Greening Program from year 2011 to 2018 in a form of shapefiles. Shapefiles are composed of .shp, .shx, and .dbf files which are a collection of polygons, points and lines that contains information on the activities done by NGP during the Site Assessment and Site Mapping Procedure (SMP), Species Selection and Spacing, Seedling Production and Nursery Establishment, Plantation Establishment, and Maintenance and Protection based on the recorded latitude and longitude of the barangays within the province of Pampanga. From the .dbf file, the following data were extracted using MS Excel: Region, District, PENRO, Barangay, Municipality, Province, Area, Name of Organization, Type of Organization, Component, Commodity, Species, Year, Zone, Tenure, Remarks, Area

January-February 2020
ISSN: 0193-4120 Page No. 4241 - 4250

Code, Species Replanted, Category, Unique ID, Longitude, and Latitude.

Using WEKA Select Attributes and Ranker methods, predictors were ranked based on their significant contributions on the size of the rehabilitated forestland based on historical data from 2016 to 2018. 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 2.

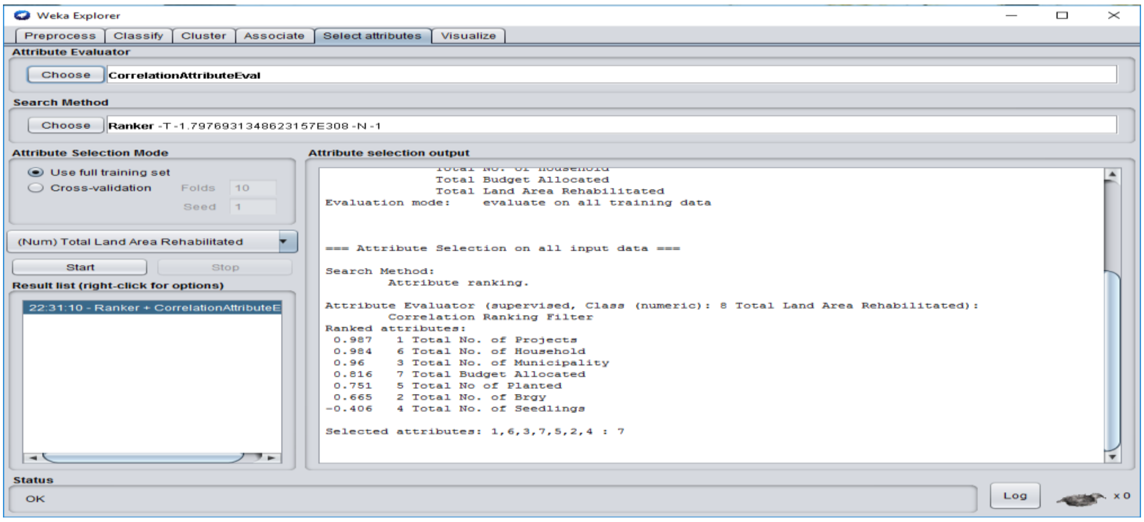


Fig 2. WEKA Select Attributes and Ranker Methods

After which, WEKA Classifier – Multilayer Perceptron was applied to generate Neural Network Single-Hidden Layer with corresponding sigmoid nodes as illustrated in Fig 3

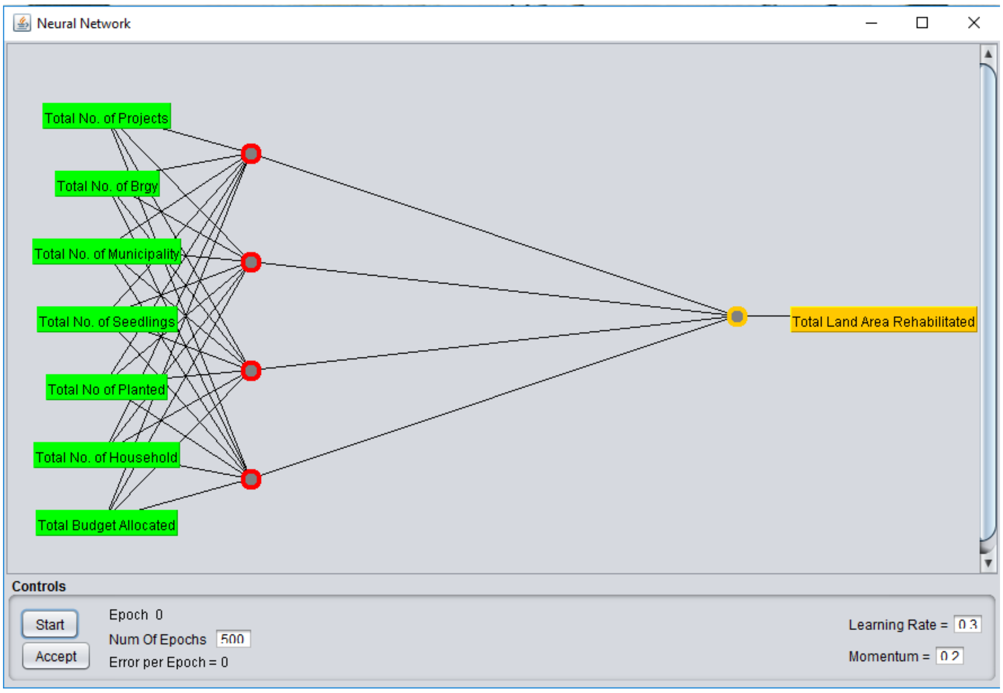


Fig 3. Multilayer Perceptron with Single-Hidden Layer for Forestland Rehabilitation

As shown in the generated diagram in Fig 3, to forecast the 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 were used in the development of the forecasting model particularly the back-propagation algorithm.

Fig 4 shows the sigmoid nodes weights and threshold which were utilized in the computation shown in Figures 5 and 6, both for Feedforward algorithm and Bak-propagation Algorithm

January-February 2020
ISSN: 0193-4120 Page No. 4241 - 4250

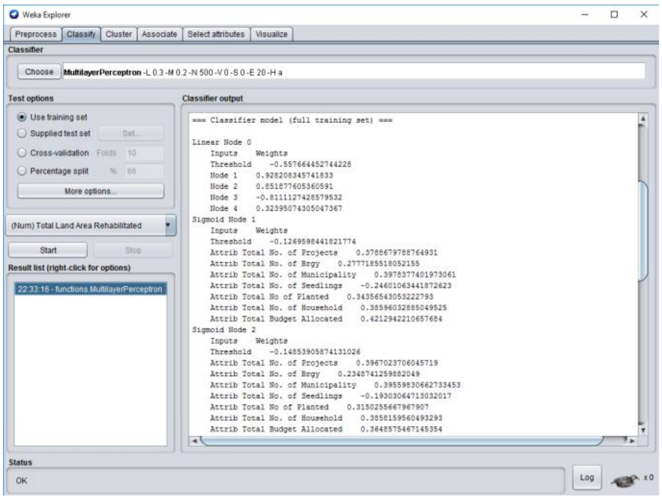


Fig 4. Sigmoid weights and threshold values

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

Artificial Neural Network with Feedforward and Back-Propagation Algorithms

After data cleaning and extraction and identifying the top factors or predictors affecting the size of the rehabilitated forestland which were done using WEKA, a forecasting model was developed. Using the Classifier, Multilayer Perceptron method of WEKA, a diagram for Neural Network was generated illustrating or showing the number of nodes of the hidden layer and providing the sigmoid weights and threshold. Outputs produced by WEKA and ANN are explained in the Results and Discussion section.

Figures 5 and 6 illustrate the computation formula of Feedforward Algorithm and Back-Propagation Algorithm, both were applied in the development of the forecasting model for forestland rehabilitation.

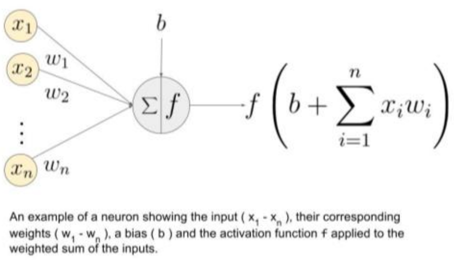


Fig 5. Feedforward Neural Network

NGP data from 2016 to 2018 were fed to this formula to generate forecast on the possible change in the rehabilitated size of the forestland in the province. However, a higher error rate was obtained from Feedforward algorithm formula thus, back-propagation was implemented to lessen or minimize error and to achieve more realistic value on the rehabilitated size

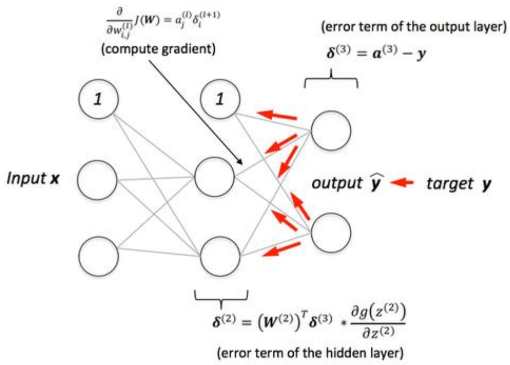


Fig 6. Back-Propagation Algorithm Neural Network

Fig 6 shows Back Propagation (BackProp) Algorithm where the first process is to apply the inputs and the desired result or output (Feedforward algorithm output). The inputs were then fed to the neurons composing of the hidden layer and a response were passed through an output layer. It was then compared to the target output and the difference were calculated using an error signal.

The algorithm then computed the error changes depending on the response of the neurons thus so far, a forward computation. The algorithm then moved back one layer and recalculated the weight to minimize the error in the output. This is a repetitive process until the input is reached and the weights become steady. The back-propagation approach was implemented through the Excel Data Solver Parameters and GRG Non-Linear Method;

January-February 2020
ISSN: 0193-4120 Page No. 4241 - 4250

Spatiotemporal Data Analysis and Visualization using the NGP Shapefiles

Using the geo-tagged photos from the NGP, longitude and latitude coordinates of the rehabilitated forestland were identified and were mapped using ArcMap where the shapefiles were formed. Also using the GIS feature of Excel, shapefiles were plotted using the .shp files. The map was formed with several layers sorted out by year. The visualization shows the progress of the projects done by the National Greening Program from 2011-2018, shown on Fig 9 in the Results and Discussion.

I. Results And Discussions

A. Pre-processing

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.

As shown in Fig 7, year 2013 has the highest total rehabilitated area gained from all the municipalities of Pampanga followed by the year 2015, 2014, 2018, and 2017. This means that there were more projects and municipalities and barangays participated in the rehabilitation program of the NGP Pampanga

A. Spatiotemporal Visualization and Graphs

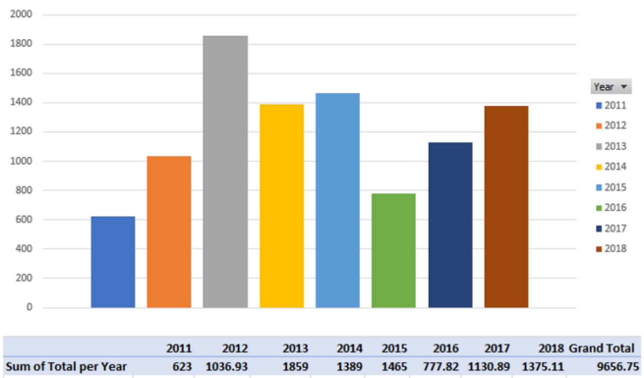
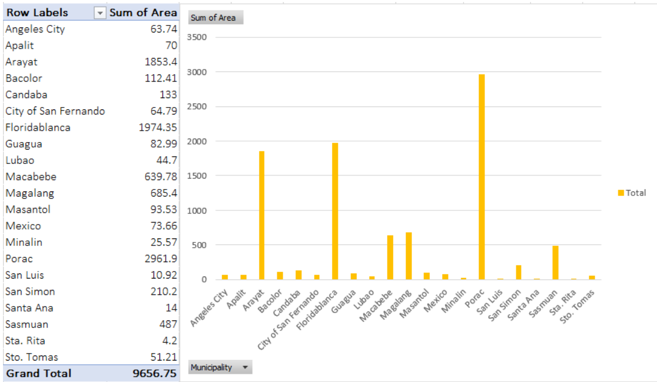


Fig 7. Total Rehabilitated Area (in ha) per Year

Fig 8 shows that Porac has the highest rehabilitated forestland due to its land area which is followed by Floridablanca and Arayat which also have bigger size of land area, from years 2011 to 2018.

January-February 2020
ISSN: 0193-4120 Page No. 4241 - 4250



Row Labels	Sum of Area
Angeles City	63.74
Apalit	70
Arayat	1853.4
Bacolor	112.41
Candaba	133
City of San Fernando	64.79
Floridablanca	1974.35
Guagua	82.99
Lubao	44.7
Macabebe	639.78
Magalang	685.4
Masantol	93.53
Mexico	73.66
Minalin	25.57
Porac	2961.9
San Luis	10.92
San Simon	210.2
Santa Ana	14
Sasmuan	487
Sta. Rita	4.2
Sto. Tomas	51.21
Grand Total	9656.75

Fig 8. Total Rehabilitated Area (in ha) per Municipality

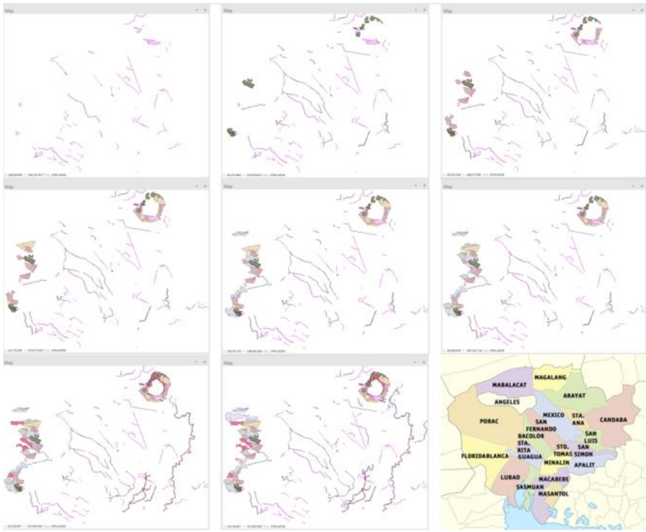


Fig 9. Spatiotemporal Visualization of the Rehabilitated Forestland from 2011 to 2018 including the flat map of the province of Pampanga indicating the municipalities

Deriving from the spatiotemporal visualization on Fig 9 Porac, Floridablanca and Arayat have the biggest or highest contribution in rehabilitating the forestland in Pampanga. Fig 8 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 on Fig 8 and as shown in the map of Pampanga in Fig 9. 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.

A. Forecasted Size or Area of Rehabilitated Forestland

Using the back-propagation algorithm and applying the weights of the predictors and sigmoid nodes' threshold, the model to forecast possible increase in the forestland rehabilitation was developed. Back-propagation was executed using Excel, Data Solver Parameters and GRG Non-Linear Method. Weights and input data were adjusted and played out until a more realistic value or forecast have attained, thus the formation of the forecasting model.

Tables 3 and 4 show sample forecasted value for additional rehabilitated area or size in Pampanga given the input values. The number of municipalities already optimized its maximum value, seemingly only the number of projects and barangays were adjusted and created 23% increase in the size of the rehabilitated forestland based from the previous forecast.

Table 3 Sample Forecast Value for Additional Rehabilitated Area/Size in Pampanga

Predictors	**Assigned/Forecasted Value**
Total No. of Projects	48
Total No. of Barangay	92
Total No. of Municipality	19

TEST Engineering & Management

January-February 2020
ISSN: 0193-4120 Page No. 4241 - 4250

Total No. of Seedlings	1237549
Total No. Planted	125005
Total No. of Household	690
Total Budget Allocated	16437410
Additional Rehabilitated Forestland in Ha	129.45

Table 4 Sample Forecast Value for Additional Rehabilitated Area/Size in Pampanga

Predictors	**Assigned/Forecasted Value**
Total No. of Projects	60
Total No. of Barangay	120
Total No. of Municipality	19
Total No. of Seedlings	1237549
Total No. Planted	125005
Total No. of Household	690
Total Budget Allocated	16437410
Additional Rehabilitated Forestland in Ha	159.30

Weight Node 1	Weight Node 2	Weight Node 3	Weight Node 4	net SUM(W*X)	b Threshold	Input plus Threshold	Sigmoid Output of the network	Activation
0.9282	0.8519	-0.8111127	0.323951	0.116571611	-0.55766	-0.44109284	0.608519402	1
0.9282	0.8519	-0.8111127	0.323951	0.137181075	-0.55766	-0.42048338	0.603598912	1
0.9282	0.8519	-0.8111127	0.323951	1.255569159	-0.55766	0.69790471	0.332276945	1

Node1	Node2	Node3	Node4	Threshold	Output by the network	MSE	Error Rate
6986291	6083486	-3196503	2848666	-0.55766445	12,721,938.25	161,958,579,961,210.00	925,057.86
212870	189694.2	-95867.9	76343.05	-0.55766445	383,038.78	161,958,579,961,210.00	33,755.59
-103466	-62633.4	57197.12	-107385	-0.55766445	(216,287.95)	161,958,579,961,210.00	27,906.94

Fig 10. Sample Feedforward Algorithm Result for 3 years data

As shown in Fig 10, forecasted value using the feedforward algorithm based from 3 years historical data resulted to a very high error rate and a negative value on the third result. Thus, back-propagation was executed to lessen error rate and to achieve more realistic value for the forecasted rehabilitated size of the forestland.

Using the Excel Data Solver Parameters, GRG Non-Linear Method, inputs and weights were adjusted to create a better model and to attain more realistic forecast. Figure 8 shows that the succeeding year will increase the rehabilitated size of forestland by 159.30 ha given the following input values: Number of Projects–60; Number of Barangay–120; Number of Municipality–19; Number of Seedlings Produced–1237549; Number of Planted–125005; and Number of Households Involved–105.

Weight Node 1	Weight Node 2	Weight Node 3	Weight Node 4	net sUM(W*X)	b Threshold	Input plus Threshold	Sigmoid Output of the netwo	Activation
0.9282	0.8519	0	0.323951	0.75193163	-0.55766	0.19426718	0.451585373	1
0.9282	0.8519	0	0.323951	0.740859101	-0.55766	0.18319465	0.454328994	1
0.9282	0.8519	0	0.323951	0.494777831	-0.55766	-0.06288662	0.515716476	1
0.9282	0.8519	0	0.323951	0.248673549	0.442336	0.6910091	0.333808632	1

Node1	Node2	Node3	Node4	Threshold	Output by the network	MSE	Error Rate
28.50417	26.9017	0.113885	14.37048	-0.55766445	69.33	2,809,082.64	94.96
33.86799	30.93834	0.113885	16.30011	-0.55766445	80.66	2,809,082.64	92.87
4.349486	4.196138	0.113885	2.184175	-0.55766445	10.29	2,809,082.64	98.68
64.49026	60.35487	0.886115	33.12268	0.442335547	159.30	2,809,082.64	#DIV/0!

Fig 11. Sample Back-Propagation Result using 3 years data with Forecasted Value

From the data provided by the National Greening Program, significant factors and predictors were identified using the Ranker method of WEKA, on which the multilayer perceptron was applied and thus the forecasting model was derived through Artificial Neural Network with Back-Propagation Algorithm. Using the model with the identified factors or predictors, input values were played out which were used as basis on the forecasted possible increase or change in the size of the rehabilitated forestland which therefore could be used as a guide for strategic planning for forest management and rehabilitation. The National Greening Program Coordinator or Authorities could look on the possibilities of increasing the number of projects, number of municipalities and household involved. Based from the

January-February 2020
ISSN: 0193-4120 Page No. 4241 - 4250

model, the number of seedlings produced does not significantly affect the size of the rehabilitated forestland based on the weights and threshold assigned by the Multilayer Perceptron method of WEKA to it which is -0.2460. Moreover, the number of households and allocated budget depends on the number of projects initiated and executed. Thus, the model suggests that to increase the size of the rehabilitated forestland, there should be more households and municipalities be involved and more projects should be done, thus requiring budget to be allocated.

Moreover, spatiotemporal visualization was considered a better way to represent data and to make the common people or the public becomes aware of the projects done of the NGP as well as the status of the forestland in the province. Numbers and Statistics can accurately present data and report however, visualizations, figures and images could make the public more aware and grasped the report more easily and could analyze changes happening in the forestland by municipality better and clearer as shown in the provided figures in the Results section.

With these two approaches, Forecasting Model and Spatiotemporal Visualization, NGP Authorities could have wider view and alternative method in presenting their data and have more options from where they could base their decision for planning and implementing forestland strategies and management approaches like how many projects should be implemented, how many households and municipalities should be involved and what kind of species could be planted in a specific barangay and be able to identify the possible increase in size of the rehabilitated forestland.

CONCLUSION

With the historical data of the National Greening Program enabled the researcher to utilized tools such as WEKA and implemented Artificial Neural Network with Back-Propagation Algorithm to it. The said data were used as test data to form or develop a forecasting model. And through the Attribute Selection, Ranker of WEKA significant factors were identified and using the Multilayer Perceptron Neural Network of the same tool, a four sigmoid node single hidden layer was generated with corresponding weights and threshold which were applied in the execution of the back-propagation algorithm.

The process of determining the significant factors is crucial since it could suggest to authorities and National Greening Program officials where to focus and they could use the result to analyze or plan a more effective strategy in forest management and rehabilitation. The predictors and factors may be used as bases in decision making such as how many projects should be done yearly, how many municipalities, household involved and seedlings to be planted in order to meet a specific change or increase in the size of the rehabilitation of forestland.

Lastly, Artificial Neural Network with Back-propagation algorithm was adopted in this study since it has the ability to model non-linear and complex relationships in which one thing does not clearly or directly follow from another such as the number of municipalities involved, number of seedlings planted and household involved. ANN can generalize after learning from the initial inputs. Using the back-propagation algorithm, more realistic forecast value on the possible increase in the size of the rehabilitated forestland was attained, after executing Excel Data Solver Parameter and applying GRG Non-Linear method several times.

I. FUTURE DIRECTION

A dynamic and interactive web application should be implemented to accommodate monitoring and viewing of information such as top performing municipalities, number of projects done within a municipality per year, species planted in municipality per year or per project, number of households involved per project and per municipality which could easily be accessed by the public thus attaining one of the objectives of the NGP - “Promote public awareness as well as instill social and environmental consciousness of the value of forests and watersheds”.

II. AUTHOR’S NOTE

This paper is just a part of a bigger research study that involves development of a web application, as mentioned in the Conclusion and Recommendation section of this paper, where the forecasting model developed using the ANN will be incorporated. The web application prototype will serve as a framework to other provinces so the NGP projects may be promoted and be known to the people. The activities done in this study specifically the spatiotemporal data analysis and development of a forecasting model for forestland rehabilitation were just the first two phases out of five phases from the conceptual framework of the bigger research study. And this study is part of the requirements in the completion of the Doctor of Information Technology (DIT) Program in Angeles University Foundation. The researcher is targeting the completion of the bigger study that involves web application by March 2020 following the study plan provided to the Commission on Higher Education (CHED) in compliance to the K-12 Scholarship Program Requirements.

III. ACKNOWLEDGEMENT

The researcher extends her heartfelt gratitude to the following: National Greening Program of Pampanga for providing the necessary data needed to complete this study; Ms. Mary Ann F. Quioc, DIT and former Research Coordinator of Mabalacat City College in Pampanga for the guidance and insights she provided to the researcher to have a better understanding and direction in the execution of this research; Dr. Gilbert M. Tumibay, the researcher’s adviser; Graduate School of Angeles University Foundation; Holy Angel University for the support and providing the researcher the study leave privilege; and Commission on Higher Education (CHED) Region 3 for the Scholarship Program and Grants

REFERENCES

[1] Gulia, P. (2018). Big Data Analytics in Action. (February), 266–294. https://doi.org/10.4018/978-1-5225-7609-9.ch009
[2] Malgaonkar, S., Soral, S., Sumeet, S., & Parekhji, T. (2016). Study on big data analytics research domains. 2016 5th International Conference on Reliability, Infocom Technologies and Optimization, ICRITO 2016: Trends and Future Directions, 200–206. https://doi.org/10.1109/ICRITO.2016.7784952
[3] P., D., & Ahmed, K. (2016). A Survey on Big Data Analytics: Challenges, Open Research Issues and Tools. International Journal of Advanced Computer Science and Applications, 7(2). https://doi.org/10.14569/ijacsa.2016.070267
[4] Ferreira, K. R., De Oliveira, A. G., Monteiro, A. M. V., & De Almeida, D. B. F. C. (2015). Temporal GIS and spatiotemporal data sources. Proceedings of the Brazilian Symposium on GeoInformatics, 2015-Novem(April 2017), 1–13.
[5] Ferreira, K. R., Oliveira, A. G. De, Miguel, A., Monteiro, V., & Almeida, D. B. F. C. De. (2016). TEMPORAL GIS AND SPATIOTEMPORAL DATA SOURCES SIG Temporal e Fonte de Dados Espaço-temporais. (2014), 1191–1202.
[6] Amini Parsa, V., Yavari, A., & Nejadi, A. (2016). Spatio-temporal analysis of land use/land cover pattern changes in Arasbaran Biosphere Reserve: Iran. Modeling Earth Systems and Environment, 2(4), 1–13. https://doi.org/10.1007/s40808-016-0227-2
[7] Lindstrom, J., Szpiro, A., Sampson, P. D., Bergen, S., & Sheppard, L. (2013). SpatioTemporal : An R Package for Spatio-Temporal Modelling of Air-Pollution. CRAN Vignettes, 1–34.
[8] Kuzniar, K., & Zajac, M. (2015). Some methods of pre-processing input data for neural networks. Computer Assisted Methods in Engineering and Science, 22, 141–151. Retrieved from http://cames.ippt.gov.pl/index.php/cames/article/view/33
[9] Kukkonen, M., & Käyhkö, N. (2014). Spatio-temporal analysis of forest changes in contrasting land use regimes of Zanzibar, Tanzania. Applied Geography, 55, 193–202. https://doi.org/10.1016/j.apgeog.2014.09.013
[10] König, C., Weigelt, P., Schrader, J., Taylor, A., Kattge, J., & Kreft, H. (2019). Biodiversity data integration—the significance of data resolution and domain. PLoS Biology, Vol. 17. https://doi.org/10.1371/journal.pbio.3000183
[11] Yu, G., Yang, R., Wei, Y., Yu, D., Zhai, W., Cai, J., … Qin, J. (2018). Spatial, temporal, and spatiotemporal analysis of mumps in Guangxi Province, China, 2005-2016. BMC Infectious Diseases, 18(1), 1–13. https://doi.org/10.1186/s12879-018-3240-4
[12] Imada, A. (2014). A Literature Review : Forest Management. (1999), 9–21.
[13] Peng, C., & Wen, X. (1999). Recent Applications of Artificial Neural Networks in Forest Resource Management: An Overview. American Association for Artificial Intelligence (AAAI) Technical Report WS-99-07.
[14] UN Sustainable Goal Development 2018 Report. (n.d.).
[15] Storch, F., Dormann, C. F., & Bauhus, J. (2018). Quantifying forest structural diversity based on large-scale inventory data: A new approach to support biodiversity monitoring. Forest Ecosystems, 5(1), 1–14. https://doi.org/10.1186/s40663-018-0151-1
[16] FAO. (2012). Forest Resources Assessment 2015: Terms and Definitions. FAO Report, 36. Retrieved from www.fao.org/forestry
[17] Davies, S. (2019). International Day of Forests. Early Years Educator, Vol. 20, pp. viii–ix. https://doi.org/10.12968/eyed.2019.20.11.viii
[18] Shekhar, S., Jiang, Z., Ali, R., Eftelioglu, E., Tang, X., Gunturi, V., & Zhou, X. (2015). Spatiotemporal Data Mining: A Computational Perspective. ISPRS International Journal of Geo-Information, 4(4), 2306–2338. https://doi.org/10.3390/ijgi4042306