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Research Paper

Integrating Deterministic Approach with Data-driven and Emerging Metaheuristic Computing Algorithm for the Estimation of Uncertain Forest Knowledge

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Abstract

This research considered a critical evaluation and estimation of the forests knowledge (FK) among university students in North Cyprus using two different approaches namely; deterministic and artificial intelligence (AI) based models. For the first approach, the study broadly assessed university students' knowledge about the forest in general context, forest protection, the importance of forest, forest administration, the danger of deforestation, individual and the government has taken the responsibility of forest versus their nationalities. Primary data were collected with the aid of a structured questionnaire in line with the proposed five research questions; all the proposed research questions were adequately answered through Cross-tabulation analysis. The outcome of the result revealed that students' knowledge about forest, importance of forest, individual and government responsibility of taken care of forest has no significant effect on nationality; while on the contrarily, the result indicated that students' knowledge about forest protection, poor forest administration and danger of deforestation has significant effect on nationality. For the second approach employed the estimation of forest knowledge using three artificial intelligence (AI) models (ANN, SVM, and ANFIS) and a classical MLR model. The performance efficiency of the models was evaluated using four statistical measures. The results indicated that SVM-M1(R2=0.8893, MSE=0.0950, and R=0.9430) outperformance all the other models despite other AI based models proved reliable for the estimation of forest knowledge. Subsequently, emerging optimization algorithm called hybridized support vector regression (SVR) Harris-hawks optimization (HHO) (i.e., SVR-HHO) were used to predict the FK was employed to hybridized SVR model in order to improve the prediction accuracy of the model. The result indicated that HHO proved promising with more than 99% prediction accuracy.

Keywords: Environmental education, Forests Knowledge, Artificial Intelligence, Harris-hawks optimization, North Cyprus

1. Introduction

Forests are so essential with the diverse values and roles they play in the life of the people and the entire society that they can never be underestimated. Forests contributed a lot to the coexistence and general fitness of both man and the natural environment. The ecological units of the environment are categorized into servicing, balancing, traditional, and other secondary roles that rightly define the vast values of vegetation. These values could be commercial, societal, and ecological, which in turn enhance the viability of the administrative system of the vegetation, evaluation of trees' well-being and supervision. Defining the roles of vegetation may be confusing due to the latest vegetation

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administrative notions and workable activities that are initiated to find solutions to the confusing notions. Environmental aesthetic values, plants, and animal multiplicity are fundamental, which makes vegetation renewable or viable. More focus and management should be given to the reinforcement of tree planting and replacement where it has been exploited for various human uses. The notion of forest study should be redefined to accommodate environmental forest resources, a collaboration of environmental benefits with commercial benefits regarding forest study. Thus, there is a need to collaborate environmental teaching with an environmental practice, which could serve great value in the teaching of landscape beauty, to actualize the unification of the aims of environmental and landscape beauty for an efficient forest administrative system. Many researchers contested this ideology, especially on the possibility of actualizing effective teaching, learning, and practice on environmental beauty among concerned people [1]–[3].

The absence of landscape beautification yardsticks is the reason why the need for environmental understanding is being stressed in the issue concerning renewable trees. Other research works deal with the understanding of the environmental and life-supporting multiplicity of vegetation and necessary values indicated in the renewable plant cover administration and policy formulation procedures due to the level of awareness of people and their societal notions regarding landscape beautification. The level of people's understanding varies with respect to the benefits of vegetation and landscape beautification assessment, considering ethnic diversity and other demographic variables [4]. Further, studies that were carried out by vegetation specialist considered nationalities as prerequisites concerning respondents' belief regarding the significance, roles, and benefits of forests to man and the environment inclusively; the study categorized learners into 4 clusters comparatively like university learners that are unrelated to forest study in Korea, learners in the field of forest study in Korea, learners outside of forest study in Canada and learners within the field of forest study in Canada. These comparative studies were an eye-opener that unfolded the impact of understanding and teaching on the environmental alertness of scholars about the roles of trees and the significance of nationality on this crucial issue. Thus, the significance of the knowledge of forests among university students in North Cyprus was strongly connected with pre-existing works of academics regarding forests [5].

Besides, it is very important in this ongoing research work to have full knowledge of students about tree-plant resources, which will invariably reveal the determinant variables that give meaning to the purpose of the study. It is an empirical fact that people's demographic profiles determine their perceptions and views about forestry. Even people's way of life or lifestyle based on occupation and nationality concerning natural endowments could influence their views and perceptions concerning the administration of such natural gifts [6], [7]. The research works revealed that the evaluation of people's views about environmental endowments and administration could be essential in keeping records of people's perceptions and views about the surroundings where they reside. Thus, for adequate renewable strategies' formulation; it welcomes people involvement with strategies formulation and increases in the knowledge that will enhance views that are supportive of strategies accord, Thus creating a balance between the human being benefiting from forest products in his life and preserving them, and preventing the attack and cutting them [8], as well as developing and improving the performance of universities participating in discussions, conferences and dialogues on forests and communication with other universities and partnership with sectors and institutions related to forests [9]. Most research works relate natural factors and events with people's beliefs, which could be limited by the method being used for evaluating beliefs, natural events and interrelationships that follow, such as interconnecting chemical airspace contamination with human displeasure [10].

Based on the developed literature, various deterministic classical linear analyses have been widely established, which have generally been reported as being associated with low estimation accuracy. This necessitates the development of a strong, accurate and non-linear hydro-environmental method known as the artificial intelligence (AI) approach. In parallel with this, different types of AI-based models have been explored in different applications related to forest sustainable management which predominantly used artificial neural networks (ANN) for example, sustainable forest management [11] , socio-ecological system [12], forest change [13], and forest resources management [14]–[16]. Hence, the aim of this study is designed in two different approaches (i) To employ a deterministic approach for evaluate the knowledge of forests among university students in North Cyprus. This is

to ascertain the beliefs and the practices of the students toward forests from a national perspective. The researchers are optimistic that the study will promote future nationality-based studies in the areas of environmental education and management among students from various nationalities across the globe, to develop environmental education at the grassroots, academic communities, and state, regional, and global levels. This will also cover up every loophole limiting forest protection programs, awareness, and collective responsibility in both nations. Although previous research was not little or not focused at all on assessing university students' knowledge of forests. Opportunity is widely opened now to evaluate the students based on their knowledge of the values, problems, education and taking responsibility and general attitudes about forests. (ii) To propose three different non-linear AI-based models, viz: Artificial Neural Network (ANN), Adaptive-Neuro Fuzzy Inference System (ANFIS) and support vector machine (SVM) and a conventional Multi-linear regression (MLR) model for the estimation of knowledge forest among university students in North Cyprus. It is worth mentioning that since the pronouncement of AI-based techniques, to the best of the authors' knowledge, up to date, no study has been conducted in technical literature indicating the knowledge forest application using these models. The motivation of work is presented in different aspects. First, an investigation of the potential capability of AI-based modes (ANN, ANFIS, and SVM) integrated with hybridized optimization algorithms for the estimation of a knowledge forest.

2. Materials and Methods

As stated above, this study proposed two different approaches in order to evaluate the knowledge forest among the students in Northern Cyprus. For this reason, deterministic and AI-based models were used for both the evaluation and estimation, respectively as described in sections 2.1 and 2.2.

2.1 Deterministic Experimental Approach

This study uses both inferential and descriptive methods to evaluate findings through a structured questionnaire according to empirical observation, collection, and recording of respondents' opinions, assessments, classifications, and interpretation of data through statistical software, with no reason for any biased manipulation of the main objective and scope of the study. The research was piloted among the university students, both at the Undergraduate and Postgraduate levels in North Cyprus to share different experiences about their knowledge and views of the forest resources in their locality. North Cyprus was selected as an area of study due to the uniqueness of the university environment, and because of the proximity to the scholar catchment, similar environmental characteristics, and challenges that are commonly associated with the Mediterranean region and other nationalities in the world. This was what propelled this study to investigate the knowledge of forests among university students of multi-nationalities in North Cyprus. As earlier indicated a well-articulated questionnaire was organized both in English and Arabic, to reach out to Libyan and other Arab students who mostly speak and have taken Arabic as their national language. The questionnaires were administered randomly among university students in North Cyprus (Near East University, Cyprus International University, and Eastern Mediterranean University) without any regard for age, gender and study level differences; the study area was distinct culturally with students from Libya, other African nations (Nigeria, Cameron, Democratic Republic of Congo, Ghana, Zimbabwe, Gambia, Senegal, Somali, Rwanda, Sierra Leone, and Zambia), North Cyprus, Turkey and other Middle East nations(Iraq, Iran, Jordan, Syria, Palestine, Lebanon, Egypt, and Yemen).

The fieldwork for administering questionnaires on a face-to-face basis was supported by the voluntary assistance rendered by two university students in North Cyprus. The sum of 300 questionnaires was administered to the university students in the targeted study area for weeks, and it takes at most fifteen minutes for the questionnaire to be answered by each participant. Most importantly, to create leading questionnaire that will answer to the fundamental objectives of the study according to the research questions; a well-structured questionnaire was developed and subdivided into seven sections with questions and responses as sub-headed which include demographic characteristics of students, evaluation of students' knowledge toward general knowledge of forests, forest protection, importance of forests, poor forest administration, danger of deforestation, and the practices of taking responsibility about forests by individual and government. Thus, to be able to acknowledge the opinions of the students toward the theme of study, participants were given the privilege of several options in making their views known for assessment; such as Yes, No and Not Sure; Agree, Disagree, and No option Count; these options are responding to some values and activities regarding forest resources [17]. In addition, the research test of reliability could be limited by the way the information from the respondents was

deduced; some options created for the respondents may not necessarily or totally signify their views and some options are not enough to express their views, particularly the options of Yes, No and Not sure. Thus, this should stand as a point of reference to further any forthcoming research works [18]. Also, a one-way reliability test control will possibly not receive general acceptance and application in any empirical study [19].

2.2 Artificial Intelligence-Based Model

For any data-driven method, the knowledge of data science and analysis is quite crucial; as such, the data used for the estimation of forest knowledge in this study were obtained using the procedure described in section 2.1. Hence, this study proposes the application of four data-driven algorithms, including three non-linear models: ANN (the most widely used data-driven model), SVM (as a recently developed model), ANFIS (as a hybrid learning algorithm) and a classical model (MLR as a commonly used linear model) for the estimation of forest knowledge using different input variables. Subsequently, emerging optimization algorithms called HHO were employed to hybridize SVR model to improve the prediction accuracy of the model. The primary motivation for employing different data-intelligence models is attributed to the difficulty in understanding whether a specific model is superior to others in practice. Therefore, choosing appropriate models for a particular case can be challenging for modelers. This complexity can only be overcome by selecting and comparing different data-driven models, including the linear models, despite their weaknesses in handling highly nonlinear and complex data. For the development of the current study, Figure 1 shows the flowchart of the methods used. From the flowchart, it can be observed that the input data are collected, pre-processed and normalized based on Equation 1. The normalization of the data was conducted before the model training, which is usually performed to increase the accuracy and speed of the model.

$$y = 0.05 + \left(0.95 \times \left(\frac{x - x_{min}}{x_{max} - x_{min}}\right)\right) \quad (1)$$

where y is the normalized data, x is the measured data, x_{max} and x_{min} are the maximum and minimum values of the measured data, respectively. For the development of this study the important variables were selected based on the sensitivity analysis in which the following variables were used: Forest knowledge (FK), Forest importance to the country (FIC), Importance for recreational activities (ICA), Vital goal of forest (VGF), Government is responsible for taking care of forest problem (GRT), Sources of forest knowledge (SFK), Benefit of forest protection to man and his environment (BFE), Responsibility of individual to protect forest in their locality (RIF), Danger of cutting forest (DCF).

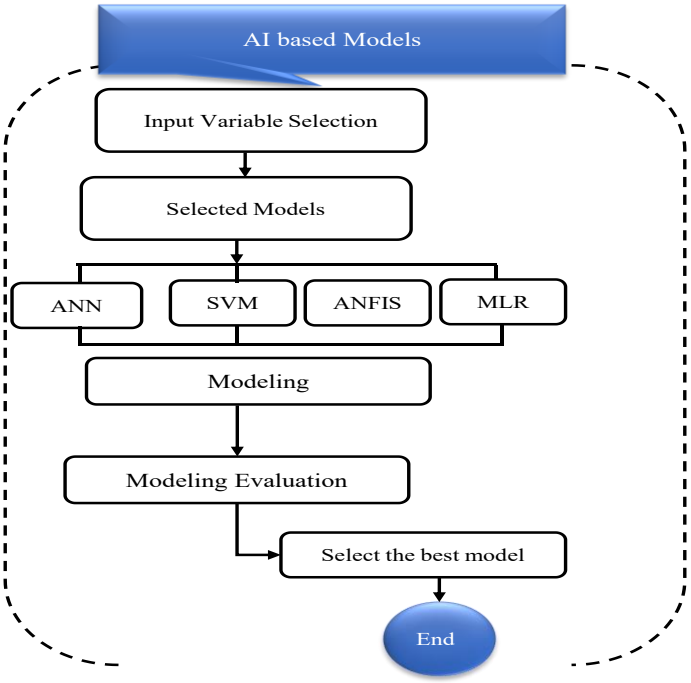


***Figure 1**: Proposed AI based models used in this study*

2.2.1 Artificial Neural Network (ANN)

ANNs are systems designed based on computational analysis to emulate the process by which human brains handle information [20]. They are comprised of different neurons as processing units, which are connected with adjustable weights and biases. ANNs serve as single or multi-layered systems consisting of an input, hidden, and output layer [21]. The present study adopts the feed-forward network with backpropagation algorithms (FFNN-BP). According to the literature, artificial neural networks are tools used in processing information, which are designed and function like the biological nervous system of the brain, and include a basic component known as a neuron (node). Due to their promising abilities, ANNs with FFNN-BP have proved to be effective tools for overcoming highly non-linear processes in different fields of science and engineering [22], [23]. The proposed ANN architecture used in this study can be presented in Figure 2.

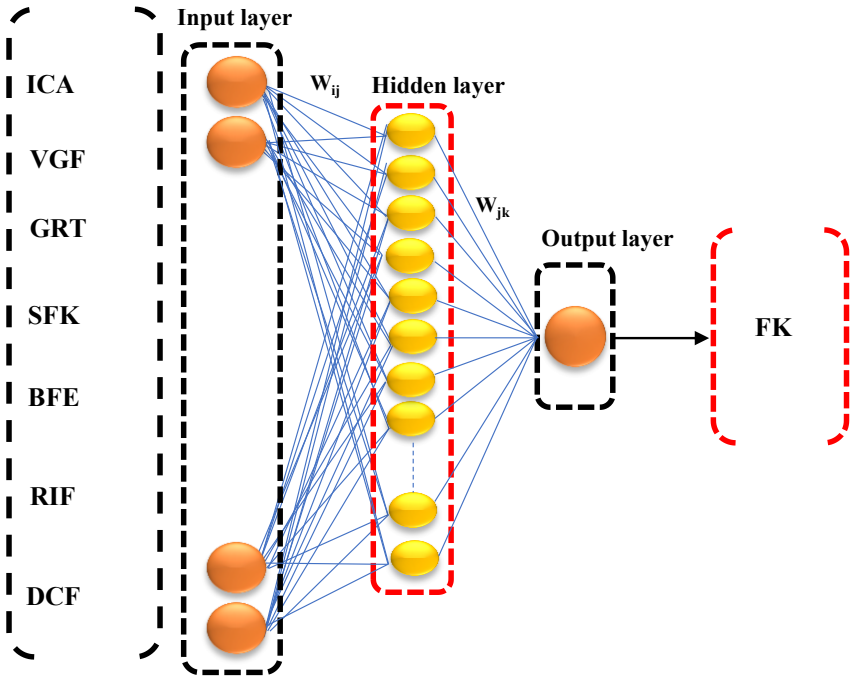


Figure 1: *Architecture of ANN used in this study*

2.2.2 Adaptive-Neuro Fuzzy Inference System (ANFIS)

One of the data-intelligence algorithms, adaptive neuro-fuzzy inference system (ANFIS) is a technique that involves the learning capacity of neural networks and fuzzy logic. ANFIS serves as a real-world estimator due to its ability to approximate real functions [24]. Generally, there are three types of ANFIS, namely Tsumoto, Sugeno, and Mamdani, where the Sugeno system has wider applications [25]. Fuzzier and defuzzifier are the major parts of the fuzzy database system. Fuzzy logic involves the conversion of input data into fuzzy values through the application of membership functions. The values range between 0-1. Nodes work as membership functions (MFs) and also permit the modeling of the relations of the input with the output. There are various types of membership functions, such as triangular, sigmoid, Gaussian, and trapezoidal [26]

Assume the FIS contains two inputs 'x' and 'y' and one output 'f', a first-order Sugeno fuzzy has the following rules.

Rule 1: if $\mu(x)$is A_1 and $\mu(y)$ B_1then $f_1 = p_1x + q_1y + r_1$ (2)

Rule 2: if $\mu(x)$is A_2 and $\mu(y)$is B_2 then $f_2 = p_2x + q_2y + r_2$ (3)

A_1, B_1, A_2, B_2 Parameters are membership functions for x and y inputs, $p_1, q_1, r_1, p_2, q_2, r_2$, are outlet function parameters. The structure and formulation of ANFIS follow a five-layer neural network arrangement. Refer to [27]–[30] for more information about ANFIS. Figure 3 presents the architecture of ANFIS used in this study.

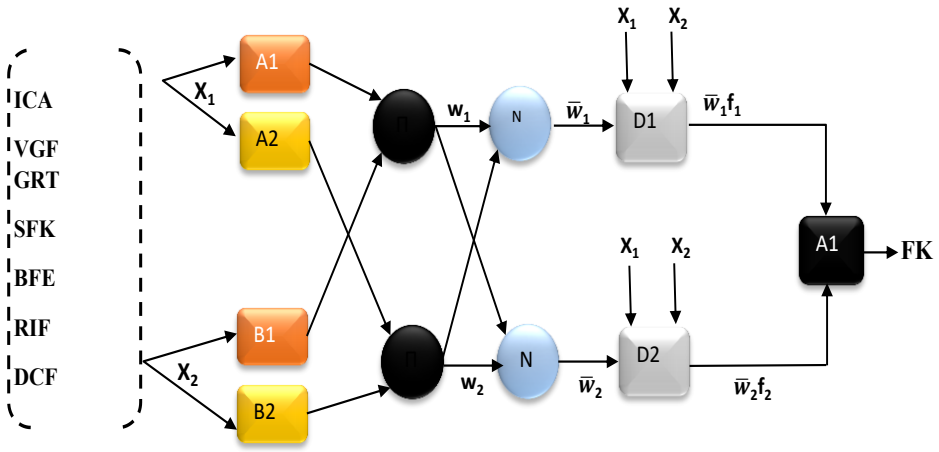


***Figure 3**: ANFIS architecture used in this study*

2.2.3 Support Vector Machine

In 1995, Vapnik proposed the idea of learning in the context of the support vector machine (SVM), which provides the desired mechanism for solving problems that involve classification, prediction, pattern recognition, and regression [31]. The SVM works according to the concept of machine learning and is composed of a data-driven model. The two major functions of SVM comprise statistical learning theory and structural risk minimization. This provides an insight that makes it different from ANN due to its capability to reduce error, redundancy of the data, and complexity, and increase the general performance of the system. SVM can be classified into linear support vector regression and non-linear support vector regression [32].

2.2.4 Multi Linear Regression (MLR)

A linear regression is considered simple if it is aimed at predicting the correlation between a single output and a single input variable. However, if the aim is to estimate the correlation between two or more input variables to determine a single criterion variable, this model is referred to as Multiple Linear Regression (MLR) [32]. MLR is the most widely utilized form of linear regression that has been used in various areas of study, in which each value of the input parameter is associated with a value of the output variable. It is worth mentioning that MLR shows a correlation in terms of a straight line, which best estimates all the data points involving both the output as well as the target variables [33]. The general form of the MLR model is as shown in Eq. (4).

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots b_ix_i \tag{4}$$

Where x_1, is the value of the *i*th predictor, b_0 is the regression constant, and b_i is the coefficient of the *i*th predictor.

2.3Harris Hawks Optimization (HHO)

Harris Hawks Optimization (HHO) is considered a novel algorithm, which is developed through mimicking the hawk's hunting procedure. The technique was used successfully for solving various intricate problems in engineering and science in recent years [35], [36]. Mostly, the hawks used to work alone, but the Harris hawks used to chase and hunt by working and cooperating [37]. Therefore, the HHO technique resembles the cooperative mechanism and hunting behavior of the natural Harris hawks. The mechanisms involved during HHO hunting consist of tracing, encircling, approaching, and attacking. This involves three main steps viz, exploration, a transition from exploration to exploitation, and exploitation (Figure 4). The first stage involves exploration, which is demonstrated as follows:

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1|X_{rand}(t) - 2r_2X(t)| \;\; if \; q \geq 0.5 \\ X_{rabbit}(t) - X_a(t) - r_3\big(LB + r_4(UB - LB)\big) \;\; if \; q < 0.5 \end{cases} \tag{5}$$

$$X_a(t) = \frac{1}{N}\sum_1^N X_i(t) \tag{6}$$

Whereby $X_a(t)$ is defined as the mean location of the Harris hawks, while the no. of Harris hawks was denoted using N, $X(t+1)$ is the location of the hawks in the following iteration $t+1$, $X_i(t)$ is the position of the current Harris Hawk at iteration t, $X_{rand}(t)$ is a randomly selected hawk, $X_{rabbit}(t)$ is the location of the rabbit (prey); LB and UB are the lower and upper bands, respectively, and q, r_1, r_2, r_3 and r_4 are random values varying between 0 and 1.

The second phase is considered a transition from exploration to exploitation, if the energy of the hawks is minimized during the hunt. The energy used for escaping the hunt can be shown as follows:

$$E = 2E_0\left(1 - \frac{t}{T}\right) \tag{7}$$

Whereby, E_0 is indicated as the original energy used during every progression ($E_0 \in (-1, 1)$), while T is the maximum size of iterations.

The exploitation stage is regarded as the third phase, and it is planned predominantly for improving local solutions in the recent solutions. During this phase, the hawks quickly attack the prey identified in the past stage based on the prey's escape and the hawk's hunting. Based on both values of E and r, the besiege type to catch the rabbit is selected; the hard one is taken when $|E| < 0.5$ and the soft one is taken when $|E| \geq 0.5$. The HHO algorithm has four strategies to mimic the attacking stage; soft besiege, soft besiege with progressive rapid dives, hard besiege, and hard besiege with progressive rapid dives (Figure 4) [34], [38][37].

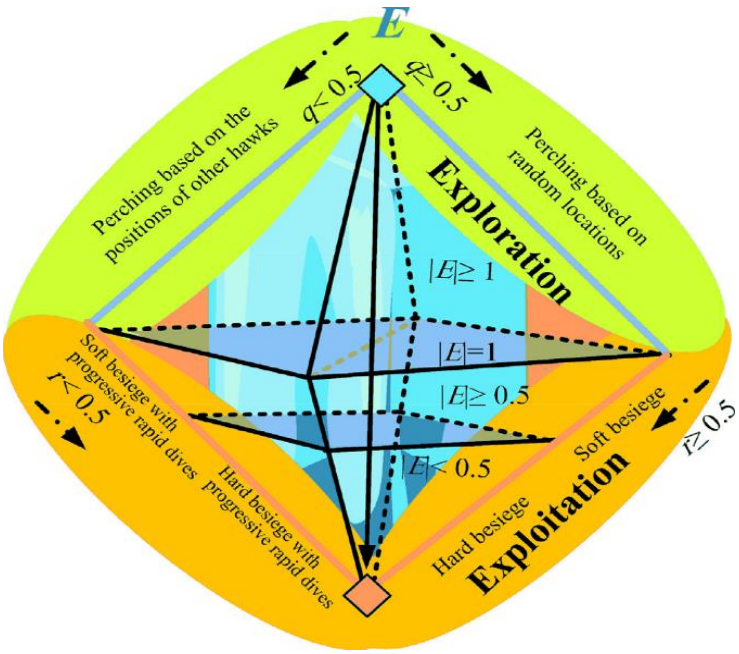


Figure 4*: Different stages of Harris Hawks Optimization [34], [36], [39], [40].*

2.4 Model Performance Criteria

For any data-driven method, the performance accuracy is evaluated using different criteria based on a comparison between the predicted and measured values[41], [42]. In this study, the determination coefficient of (R^2) and correlation coefficient (R) as a goodness-of-fit and two statistical errors, including root mean-squared error (RMSE), mean-squared error (MSE), were used for the evaluation of the models:

$$R^2 = 1 - \frac{\sum_{j=1}^{N}\left[(Y)_{obs,j} - (Y)_{com,j}\right]^2}{\sum_{j=1}^{N}\left[(Y)_{obs,j} - \overline{(Y)}_{obs,j}\right]^2} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Y_{obsi} - Y_{comi})^2}{N}} \tag{6}$$

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(Y_{obsi} - Y_{comi})^2 \tag{7}$$

$$R = \frac{\sum_{i=1}^{N}(Y_{obs}-\bar{Y}_{obs})(Y_{com}-\bar{Y}_{com})}{\sqrt{\sum_{i=1}^{N}(Y_{obs}-\bar{Y}_{obs})^2 \sum_{i=1}^{N}(Y_{com}-\bar{Y}_{com})^2}} \quad (8)$$

Where N, Y_{obsi}, $\bar{Y}$ and Y_{comi} are data number, observed data, average value of the observed data and computed values, respectively.

3.0 Application of Results and Discussion

This paper presents the first application of deterministic and AI-based models for the evaluation and estimation of forest knowledge among the students of Northern Cyprus. The results of both deterministic and AI approaches are presented in the section below.

3.1 Results and Discussion of Deterministic Approach

The deterministic analysis of this study can be categorised into demographic characteristics of the respondent, students' knowledge about forests versus nationality, students' knowledge about poor forest administration and danger of deforestation versus nationality, and students' knowledge of individual and government responsibility regarding forests and nationality. Table 1 shows the demographic characteristics of the respondents.

Table 1*: Demographic Characteristics of Students of The Near East University, Cyprus International University, and Eastern Mediterranean University*

Response	Frequency	Percentage
Gender		
Male	175	58.3%
Female	114	38.0%
Total	289	96.3%
Name of the University		
Near East University	75	25.0%
Cyprus International University	110	36.7%
Eastern Mediterranean	109	36.3%
Total	294	98.0%
Background of Education		
Undergraduate	172	57.3%
Master	84	28.0%
PhD	33	11.0%
Total	289	96.0%
Nationality		
Libya	65	21.7%
Turkish-Cypriot	60	20.0%
Turkish	58	19.3%
Middle East	51	17.0%
Africa	53	17.7%
Total	287	95.7%
Age category		
Under 21	45	15.0%
21-25	84	28.0%
26-30	73	24.3%
31-35	33	11.0%
36-40	23	7.7%
41-45	16	5.3%
45 above	9	3.0%
Total	**283**	**94.3%**

The results in Table 1 indicated a higher percentage of males over female; the educational background of the university students varied from undergraduate to Master and Ph.D. Also, students from diverse nationalities were broadly covered, which added more value, significance, and uniqueness to the course of this study; most of the nationalities across universities in North Cyprus were fairly represented within the ambit of the sample size on the average assessment, and all the students from these identified nationalities fully participated. The survey cuts across students of different age categories. There are cogent necessities to survey diversity in the knowledge of students toward vegetation resources, especially amongst universities of multinational ties, in terms of tree-plant protection, importance, administration, social responsibility, government responsibility, and destruction [43]. It has been

proven practically that university learners could possibly represent the views of people (regardless of their demographic differences) in the larger society analytically through the pragmatic survey; these will also provide an intelligent report about tree-planting on the understanding of vegetation impacts to various nations worldwide [44], [45].

Table 2*: Cross Tabulation Analysis for Forest knowledge versus Nationality (Chi-Square 0.150 greater than Alpha-value 0.005)*

	Nationality				
Students Forest knowledge Count	**Libyan Students**	**Turkish Cypriot Students**	**Turkish Students**	**Middle East Students**	**Other African Students**
Yes Count	42	30	32	24	32
Forest knowledge %	26.2%	18.8%	20.0%	15.0%	20.0%
Nationality %	67.7%	52.6%	58.2%	47.1%	61.5%
No Count	7	19	14	17	10
Forest knowledge %	10.4%	28.4%	20.9%	25.4%	14.9%
Nationality%	11.3%	33.3%	25.5%	33.3%	19.2%
Not sure Count	13	8	9	10	10
Forest knowledge %	26.0%	16.0%	18.0%	20.0%	20.0%
Nationality %	21.0%	14.0%	16.4%	19.6%	19.2%

However, the results of Cross-tabulation analysis that categorically revealed that students' knowledge about forest has no significant effect on nationality; it implies that there is no remarkable effect between forest knowledge and nationality or implies that students' knowledge about forest stand as independent variable without any association with nationality – in which P-value for the Chi-Square (0.150) is greater than the Alpha-value (0.005) (Table 2). This is because the students come from different geographical regions and nations across the world have different knowledge and views about forests. Tertiary institutions that have many multinational students are positioned globally to provide methodological understanding about forests to the students, through innovation, professionalism, public enlightenment programs, and promotion of forest activism [9], [46]. Although the overall results showed no ties of connection between students' forest knowledge and nationality because some students have a great idea about forest values, management, and social responsibility without any connection with their nationalities. Thus, any tertiary institutions that are endowed with so many multinational students need to be constantly connected with innovation on forest knowledge; these higher institutions ought to be conscious of the reformation happening around the globe, which could be achieved through collaborative works with the corporate organization, informal organizations, people, community, and activists on matters relating to forest knowledge and sustainability [47].

Knowledge about the forest is an optional thing, which could be supported by societal norms, principles, beliefs, political philosophy and nationalism. Understanding and insight about forestry could emerge from diverse ways, which in turn inspire people about the possibility of making its immediate forest endowments very sustainable over a long period. Before the advent of modernization and organized society, native people across the entire globe had devised various means of forestry and land-use that long supported their primary occupation and traditions with no adverse effects on the immediate environment [48]. Even students' understanding about forestry can be derived from natural and applied studies, social and humanities studies (such as finance and commerce, information marketing, governmental studies, commercial administration, and legal studies); these will eventually form a base of discovery and understanding for forestry program formulation and execution toward sustainability [49]. The Cross-tabulation analysis explicitly stated, according to the details in Table 3, students' knowledge about forest protection has a strongly significant effect on nationality; regardless of the diverse nationalities of the students, they firmly acknowledged that forests and their vast resources ought to be seriously protected, because they have so many tremendous values that contribute to the people and the environment. On the account of the Chi-square results, the P-value showed 0.002 which is less than the constant Alpha-value (0.005); the result statistically concluded that students' knowledge about forest protection has a remarkable impact on nationality, which could be interpreted that students' knowledge about forest protection and nationality are both dependent variables.

Table 1*: Cross Tabulation (Chi-square P-value is 0.002 less than Alpha-value 0.005) Analysis for Students' Knowledge about Forest Protection versus Nationality*

Students	**Nationality**				
Knowledge about Forest Protection Count	**Libyan Students**	**Turkish Cypriot Students**	**Turkish Students**	**Middle East Students**	**Other African Students**
Yes Count	29	22	14	17	22
Forest protection %	27.9%	21.2%	13.5%	16.3%	21.2%
Nationality %	50.0%	42.3%	28.0%	37.8%	42.3%
No Count	26	25	31	23	16
Forest protection %	21.5%	20.7%	25.6%	19.0%	13.2%
Nationality%	44.8%	48.1%	62.0%	51.1%	32.0%
Not sure Count	3	5	5	5	12
Forest protection %	10.0%	16.7%	16.7%	16.7%	40.0%
Nationality %	5.2%	9.6%	10.0%	11.1%	24.0%

In addition to the above analysis, there are so many people globally from different environments and professions, especially students of diverse nationalities, who have the same motive for vegetation conservation; the necessity and liberality may not be the same, but their agenda is in line with the general forestry conservation. Probably, occupation and sources of revenue may not be the same [50]. Also, the results indicated that a strong correlation between students having or not having knowledge about forest protection has a lot do with the nations of their origin; the cultural and political practices of any nation have a significant impact or effect on citizens toward forest sustainability. With the increase in vegetation destruction worldwide, these challenges call for more studies reaching out to all nationalities to enlighten and direct all the programs of nature passionate people toward the protection of tree-plant endowments. Thus, a study of this nature that covers different ethnic groups in universities of multinational ties regarding knowledge of the forest among university students may be very rare and often cumbersome, regardless of whether such diverse ethnic groups have been previously considered for others or other empirical works elsewhere [51]. The results of the Cross-tabulation analysis about Table 4 depicted that students' knowledge about the importance of forest has no significant effect on nationality which means there is no association between importance of forest and nationality; the Chi-square showed P-value 0.067 greater than the Alpha-value 0.005; the conclusion and implication of this result indicated that students' knowledge about the importance of forest has no significant effect on their nationality.

Table 2*: Cross Tabulation (Chi-square P-value 0.067 greater than the Alpha-value 0.005) Analysis of Students Knowledge about the importance of Forest versus Nationality*

Students Knowledge about the importance of Forest Count	**Nationality**				
	Libyan Students	**Turkish Cypriot Students**	**Turkish Students**	**Middle East Students**	**Other African Students**
Yes Count	29	34	32	25	18
Forests are important to the economy, humans and the environment %	18.1%	24.6%	23.2%	21.0%	13.0%
Nationality %	47.5%	63.0%	64.0%	50.0%	34.6%
No Count	28	18	13	20	28
Forests are important to the economy, humans and the environment %	26.2%	16.8%	12.1%	18.7%	26.2%
Nationality%	45.9%	33.3%	26.0%	40.0%	53.8%
Not sure Count	4	2	5	5	6
Forests are important to the economy, humans and the environment %	18.2%	9.1%	22.7%	22.7%	27.3%
Nationality %	6.6%	3.7%	10.0%	10.0%	11.5%

Also, a wide margin of students from different nationalities attested with a Yes count on how forests and its resources are extremely important to the economy, human, and environment. Most importantly, with much regard for the students' diversity in nationality and demographic characteristics, there always exist those great connections betwixt forestry reserves impact and human continuous survival and a sustainable environment (Table 5). Many research works that were conducted in advanced and developing nations concerning the people knowledge about forestry impacts – the aftermaths of the research depicted an incredible result that the people have more regards for forestry endowments both financially, socially, environmentally and medically; also, students' knowledge about the importance of vegetation could strongly be determined by their perceptions, traditions, faith, principles, and exposures [52], [53].

Table 3*: Cross Tabulation (Chi-square P-value 0.191 Greater than the Alpha-value 0.005) Analysis Students' Knowledge about Poor Forest Administration and Danger of Deforestation versus Nationality*

	Libyan Students	Turkish-Cypriot Students	Turkish Students	Middle East Students	Other African Students
Agree	50	50	46	40	43
Poor forest administration and Danger of Deforestation %	21.8%	21.8%	20.1%	17.5%	18.8%
Nationality %	78.1%	86.2%	85.2%	80.0%	81.1%
Disagree	11	6	6	3	8
Poor forest administration and Danger of Deforestation %	32.4%	17.6%	17.6%	8.8%	23.5%
Nationality%	17.2%	10.3%	11.1%	6.0%	15.1%
No Opinion	3	2	2	7	2
Poor forest administration and Danger of Deforestation %	18.8%	12.5%	12.5%	43.8%	12.5%
Nationality %	4.7%	3.4%	3.7%	14.0%	3.8%

The results of the cross-tabulation finally indicated with Chi-square P-value of 0.191, which is greater than the Alpha-value of 0.005; this critically concluded that students' knowledge about poor forest administration and danger of deforestation has no significant effect on nationality – this implies that the identified variables functioned independently. The results of the Cross tabulation revealed that the students Agree Count was more remarkably higher on percentage rating than Disagree and No option count based on poor forest administration and danger of deforestation versus nationality; Thus, it is quite cumbersome considering the above reports administering vegetation resources at a continuous supporting capacity – due to policy and obligation differences among diverse concern groups and students; this is posing serious risk to forestry and other related vegetation endowments as a result of diverse consequences of climatic variation, persistent lumbering activities, urbanization, rapid human growth in headcount, poor forestry, failure of state governance, lack of grass roots and academic environments involvement and lack of legal frame on tree-plant sustainability. Poor forestry is a clear issue affecting the global communities (including several African, South American, Asian, European, and Middle-East and North American nations) in attaining sustainable forestry, because of a lack of valuable information and other related tips of environmental information on forestry [54], [55]. From a nationalist perspective, this implies that there should be a strong public push from academic institutions, native people, environmental activists, private social institutions and corporate profit-making firms; all these interest groups could work in collaboration with the state forest administration toward combating deforestation and reinforcing policy that will enhance forest restoration. Adversely, several nations worldwide are not working efficiently toward these aforementioned suggestions based on funding, policy-making, implementation and human capability building – to convey their proposed plan and program on forest administration [56].

Table 4*: Cross Tabulation (Chi-square P-value 0.295 Greater than the Alpha-value 0.005) Analysis Students Knowledge of Individual and Government Responsibility of Forest Versus Nationality*

	Nationality				
Students' Knowledge of Individual and Government Responsibility of Forest versus Nationality Count	**Libyan Students**	**Turkish-Cyprus Students**	**Turkish Students**	**Middle East Students**	**Other African Students**
Yes Count	51	37	39	44	40
Individual and Government responsibility to take care of forest %	24.2%	17.5%	18.5%	20.9%	19.0%
Nationality %	82.3%	69.8%	75.0%	86.3%	75.5%
No Count	8	11	10	3	6
Individual and Government responsibility to take care of forest %	21.1%	28.9%	26.3%	7.9%	15.8%
Nationality%	12.9%	20.8%	19.2%	5.9%	11.3%
Not sure Count	3	5	3	4	7
Individual and Government responsibility to take care of forest %	13.6%	22.7%	13.6%	18.2%	31.8%
Nationality %	4.8%	9.4%	5.8%	7.8%	13.2%

The cross-tabulation analytical results disclosed that students' knowledge about individual and government responsibility to take care of the forest has no significant effect on nationality, which indicated a Chi-square critical P-value as 0.295 is greater than the Alpha-value of 0.005. In the actual sense, nationality is not a determining factor that could influence people's knowledge, both as individuals or governments among various nationalities; it is thus concluded that individual and government responsibility to take care of the forest has no remarkable impact on nationality. Academic communities, relatives, government and other civic organizations are usually expected and obliged to play a crucial role in enlightening learners on norms, traditions, and principles governing a given society or state [57].State administration in the context of taken responsibility, the state authority on natural vegetation played a crucial responsibility in the areas of logistics and administration, decision making and legal framework, execution of programs, and creating conducive atmosphere for effective tree-plant administration; so, state administration are central controller of vegetation endowments – they even carry larger responsibilities than the students and other concern groups in the society [58], taking responsibility of caring for the forest either by an individual or public institution could be a constitutional duty from the perspective of citizenry or nationalism, and could be regarded as a voluntary activity that proves a sense of self-responsibility. Social obligation, either on the part of the individual or the government to care for the forest – it is never any way connected to understanding or wisdom; to a certain extent, it is a feature that defined several manners or attitudes; thus, it is internal attribute of an individual being determined by societal principles; such principles could be ethical or nationalistic in nature [57]. This concept of social obligation could encourage students to take positive steps or tasks toward taking care of the forest and other environmental resources.

3.2 Results of AI-Based Models

For the development of the data-driven models, MATLAB 9.3 (R2019a) was employed in the ANN, SVM, and ANFIS models, while the deterministic linear MLR model was developed using the simulation tool in the EViews software 9.5. According to [24], obtaining suitable hidden nodes is the crucial aspect of any ANN modeling in order to avoid overfitting caused by different factors. As has been reported in several works of literature in the field of science and engineering, there is no particular standard method for determining the appropriate number of hidden neurons**.** According to [59] [60], the proper number of nodes in the hidden layer ranges from $(2n^{1/2} + m)$ to $(2n+1)$ for the identification of the optimum number of hidden layers, where n is the number of input neurons and m is the number of output neurons. Hence, 5-21 was found to be the range of the hidden neurons of the ANN model for the estimation of forest knowledge (FK). Furthermore, the appropriate and optimal determination of parameters (Cε, γ) in the SVM models is very important in choosing the best structure for the models. In this research, optimal values were obtained by employing the kernel function of the grid procedure, as suggested by [31]. For ANFIS modeling, various types of membership functions (MFs) and epoch iteration were explored using trial and error to identify the best structure. The modeling comprises of

two different models' combinations (M1 and M2) in which M1 contained five variable combinations (FIC, ICA, BFE, DCF, and GRT) and M1 contained eight variables (FIC, ICA, BFE, DCF, GRT, VGF, RIF, and SFK). The sensitivity analysis was performed to determine the combination of the models that as presented in Table 7. Sensitivity using correlation describes how well the relationship between the variables can be described using a linear function. The strength of the correlation is not dependent on the direction or sign. A positive coefficient indicates that an increase in the first parameter would correspond to an increase in the second parameter, while a negative coefficient indicates an inverse relationship whereby one parameter increases and the second parameter decreases [61]. It can be seen from Table 7 that the high correlation between target variables FK could be attributed to the combination of M1, then subsequently M2.

Table 5*: Spearman Pearson correlation analysis between the variables*

Variables	*FIC*	*ICA*	*VGF*	*GRT*	*SFK*	*BFE*	*RIF*	*DCF*	*FK*
FIC	1								
ICA	0.1841	1.0000							
VGF	0.0706	0.2726	1.0000						
GRT	-0.0298	-0.0611	0.0694	1.0000					
SFK	-0.0791	0.0853	0.1282	-0.0774	1.0000				
BFE	-0.1215	-0.0438	0.2815	0.0287	0.1619	1.0000			
RIF	-0.0112	0.0387	-0.1667	0.0970	-0.1187	-0.2943	1.0000		
DCF	-0.2425	-0.0228	0.1085	0.0544	0.1226	0.3560	-0.0075	1.0000	
FK	0.2793	0.1337	-0.1118	-0.1317	-0.0973	-0.1424	0.0970	-0.1641	1.0000

Table 8 shows the results of the performance analysis for ANN, SVM, ANFIS, and MLR models. It can be seen from the models that all three AI-based models can produce the best performance accuracy over the linear MLR model. This is due to the powerful nature of nonlinear AI-based models in capturing the complex system. Among the AI-based models, SVM-M1 emerged to be the best combination for the estimation of FK, with the values of R^2=0.8893, MSE=0.0950, and R=0.9430 in the testing phase.

Table 6*: Performance Analysis of the models*

	Training				**Testing**			
Models	**R^2**	**MSE**	**R**	**RMSE**	**R^2**	**MSE**	**R**	**RMSE**
ANN-M1	0.8482	0.1205	0.9210	0.3472	0.8026	1.0705	0.8959	1.0347
ANN-M2	0.8582	0.1126	0.9264	0.3355	0.8485	0.8215	0.9212	0.9064
SVM-M1	0.8947	0.0836	0.9459	0.2891	0.8893	0.0950	0.9430	0.3082
SVM-M2	0.5345	0.3696	0.7311	0.6079	0.6721	1.7783	0.8198	1.3335
ANFIS-M1	0.8376	0.4205	0.9152	0.6485	0.8364	0.8874	0.9145	0.9420
ANFIS-M2	0.8189	0.1438	0.9049	0.3792	0.7455	1.5518	0.8634	1.2457
MLR-M1	0.6715	0.2608	0.8195	0.5107	0.6202	2.0599	0.7875	1.4352
MLR-M2	0.5440	9.9607	0.7375	3.1561	0.5831	9.9329	0.7636	3.1516

Further analysis of the results demonstrated that ANN-M2 served as the second-best follow by ANFIS-M1 and lastly MLR-M1. The estimation results with regards to goodness-of-fit are presented with a radar chart (Figure 5). From the figure it can be concluded that the performance accuracy of the best models follows the following order: SVM-M1>ANN-M2>ANFIS-M1>MLR-M1. The MLR models was attributed to the poor results that cannot serve the estimation purpose owing to the fact that MLR is a linear model that cannot capture the nonlinear relationship between the variables. This can be proved in several technical literature [41], [62], [63], [64], [65]. To compare the predictive performance of this study the following literature [65], [66] confirm that for the good analysis of the model R values should be greater than 0.7. In addition, according to [65], [66] the R^2 greater that 0.8 is satisfactory for any analysis using AI based models.

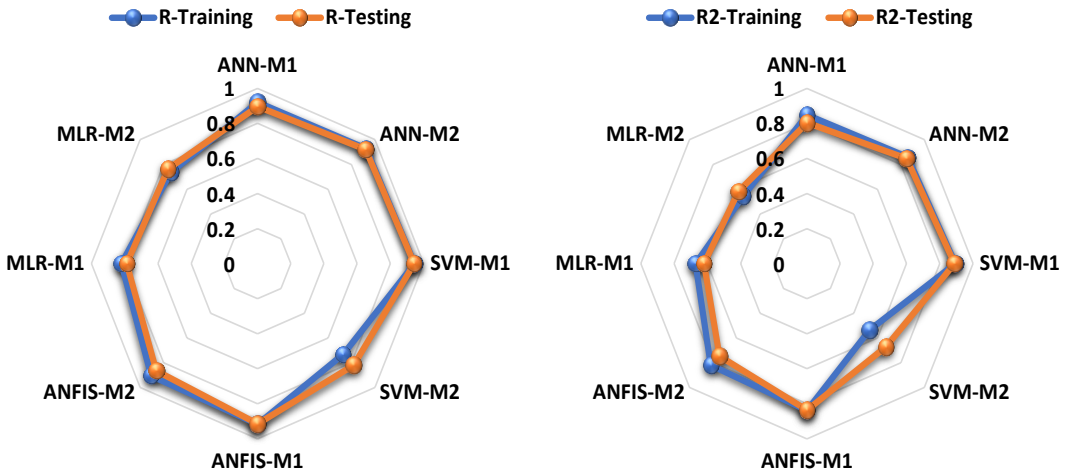
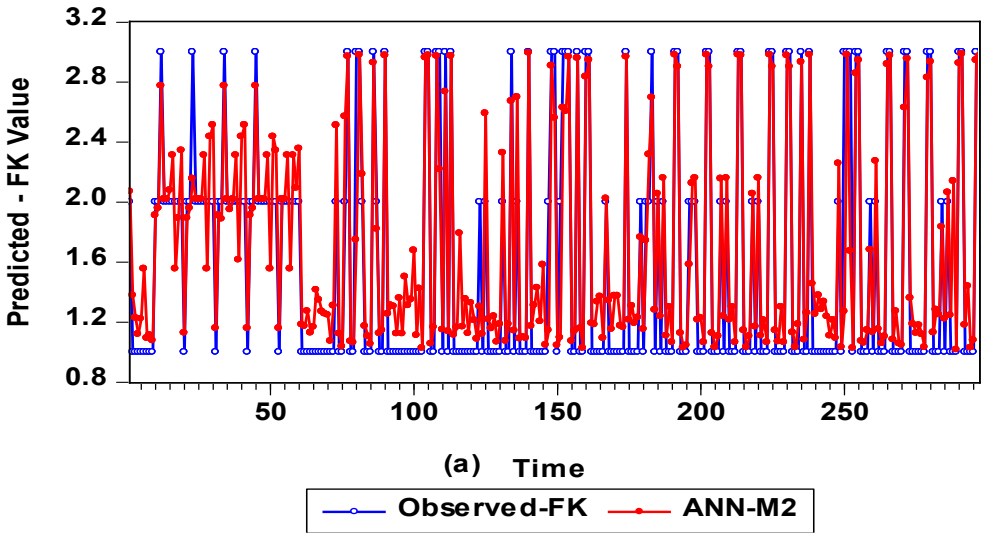


Figure 5*: Radar chart for all the models (ANN, SVM, ANFIS, and MLR)*

For more explanation about predictive analysis of the model, point by point plot are generated between the observed and the predicted values for the best models as depicted in Fig. 6. From the plots it can be observed that the high agreements between the observed and predicted values were attributed to the SVM-M1. For this reason, the quantitative analysis of the models can be generated using determination coefficient (R2). SVM-M1 increased the prediction accuracy of ANN, ANFIS, and MLR by 3%, 5%, and 22% in the training phase while in the testing phase it increased the prediction accuracy by 4%, 5%, and 26%, respectively.



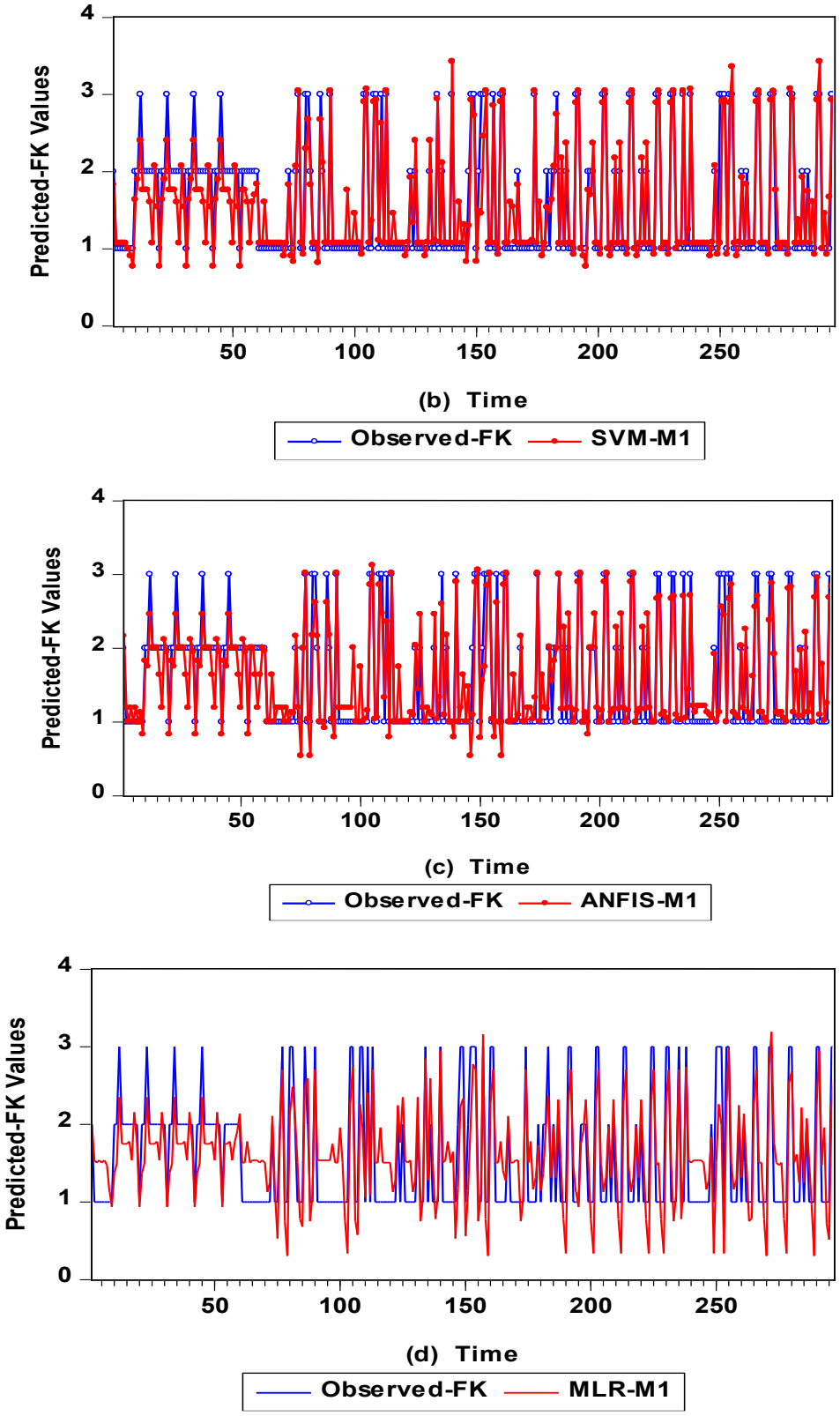


***Figure 6**: Point by point plot between the observed and predicted values for (a) ANN-M2 (b) SVM-M1 (c) ANFIS-M1, and (d) MLR-M1*

According to [24], [42], and [67], a good analysis of any predictive models contains at least one goodness-of-fit e.g. R^2, and one absolute error e.g. MSE, hence, Figure 7 presents the different variations of MSE and RMSE in both the training and testing phases. From the figure it can be seen that the MLR model emerges to be with the highest error variance, with the lowest error associated to SVM-M1. Based on the predictive comparison of the models, it is clearly shown that the non-linear models (ANN, SVM and ANFIS) outperformed the traditional linear regression model (MLR). The figure further proved that all AI models are capable of predicting the FK. It is important to note that the performance efficiency of all four models in terms of R^2, MSE, R, and RMSE shows a satisfactory and reliable accuracy. This can be due to the cross-validation process conducted before model calibration, which is very significant in model evaluation [22]. Lastly, the comparison of all the models can be demonstrated using a box-plot presentation (Figure 8).

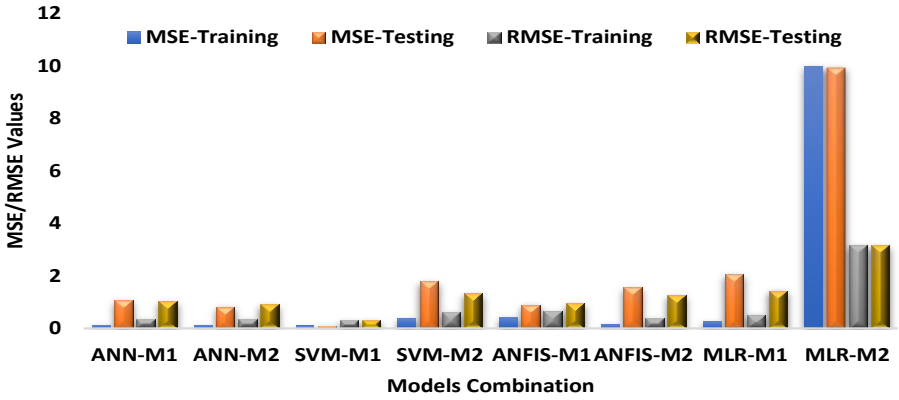


Figure 7*: Shows the error performance in term of MSE, and RMSE for all the models*

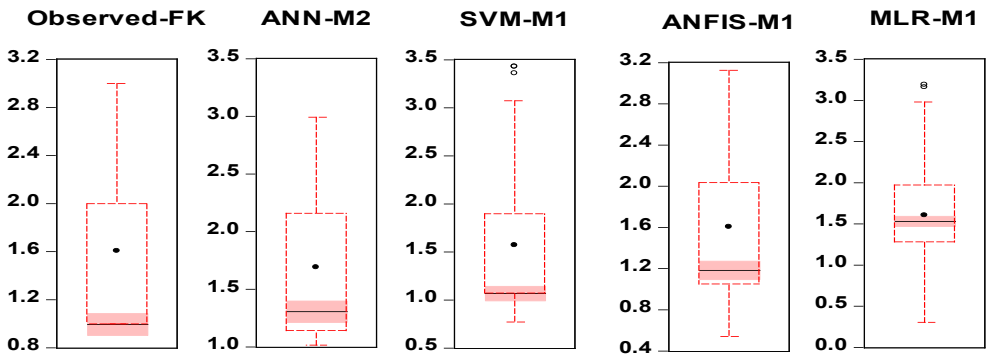


Figure 8*: Box-plot between the observed and the best predicted models for ANN, SVM, ANFIS, and MLR*

3.3 Result of Hybridized Optimization Modelling

The pre-processing of data was carried out using various methods, including normalization and reliability analysis. For computational analysis (time series data), understanding the effect of individual inputs is crucial in determining the robustness of the predictive models. Hence, stationery and reliability analysis were conducted for all the study areas using Cronbach's alpha method and unit root test (i.e., using Augmented Dickey-Fuller (ADF)). It should be noted that for any time series, the preliminary analysis of a single parameter or input is quite significant for the reason that their prediction accuracy could potentially add to the performance efficiency of the models. As reported in the literature [68], [69], the internal consistency of the parameter can be a positive impact if the Cronbach's alpha values exceed the threshold of 0.7. According to [70], to obtain reliable and valid outcomes that safeguard the stationarity of all the parameters, the ADF test is paramount. The experimental data used in the present work qualified all the aforementioned criteria

As described in the literature section, the modelling was conducted using MATLAB 9.3 (R2020a). The best architecture of SVR model was optimized and selected using the trial-and-error technique. The results of the simulation were checked and evaluated using R, and R^2 to check for the fitness between the experimental and predicted values, while MSE was employed to determine the error depicted by the models in both the training and testing stages. Based on model combinations, the simulated results in terms of quantitative assessment are presented in Table 9. From the results, it can be observed that the predictive modeling approaches have achieved different adequacy in accordance with evaluation criteria. Besides, the overall results demonstrated that SVR-HHO served as the best simulation in terms of performance criteria. Although it is difficult to rank the models in accordance with the achieved accuracies, nevertheless, the HHO approach relatively showed the best prediction accuracy, which attained more than 95% about goodness of fit. However, the comparative visualization of the model combination is presented in scatter plots (see Figure 9). A scatter plot shows the level of agreement between the observed and predicted load for the overall goodness-of-fit. It is obvious from the scatter plot that the SVR-HHO model shows higher accuracy in comparison to the SVR model.

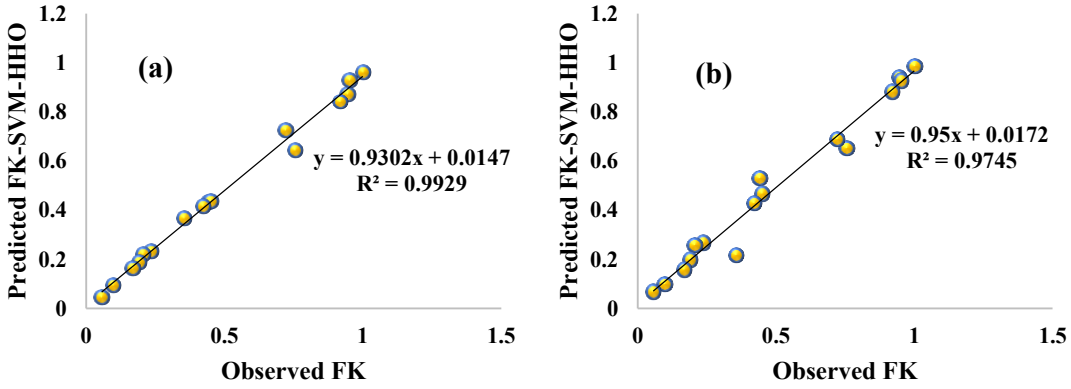


Figure 9*: Scatter graphical representation for (a) SVR (b) SVR-HHO*

Table 9. *Results of evaluation criteria for SVR, and SVR-HHO model*

	Training			Testing		
	R2	**R**	**MSE**	**R2**	**R**	**MSE**
SVR	0.9753	0.9875	0.0335	0.9753	0.9875	0.0421
SVR-HHO	0.9918	0.9958	0.023	0.9921	0.9960	0.0321

This also justified the capability of the HHO model in handling the chaotic system. In addition, MSE is a more natural measure of average error, and (unlike RMSE) is unambiguous. It is a model evaluation metric used with regression models [71]. The mean absolute error of a model with respect to a test set is the mean of the absolute values of the individual prediction errors over all instances in the test set. Table 9. also proved merit with regards to error values, as indicated by several researchers lowest values of MSE indicate the best result, and vice versa. The superiority of the SVR-HHO model can be attributed to the fact that the hybrid model has been proving to be promising than the single model. It is very important to report how reliable AI-based models are in the fields of both science and engineering. Moreover, the overall comparison between the best SVR model and the two hybrid SVR algorithms (SVR-HHO) is provided using a two-dimensional Taylor diagram, as presented in Figure10. The Taylor diagram highlights and summarizes several statistical indices such as correlation coefficient (R), RMSE, and standard deviation between the observed and computed [72]. The Taylor diagram has been utilized in various fields such as water engineering, climate, and hydrological modeling. Interestingly, to the best of the author's knowledge, this research serves as the first to use this diagram in forecasting load demand. Also, this diagram has the ability to highlight the goodness of fit of various models in comparison with one another; therefore, the diagram can be seen as a series of points on a polar plot. Detailed explanation and discussion on the Taylor diagram are given in the literature [73]. From Figure 10, it can be observed that the SVR-HHO achieved better goodness of fit in all, with the

value of R = 0.97% in the testing phase. The results lead to the conclusion that for both training and testing, SVR-HHO is capable of capturing the complex nonlinear patterns between the load demand variables.

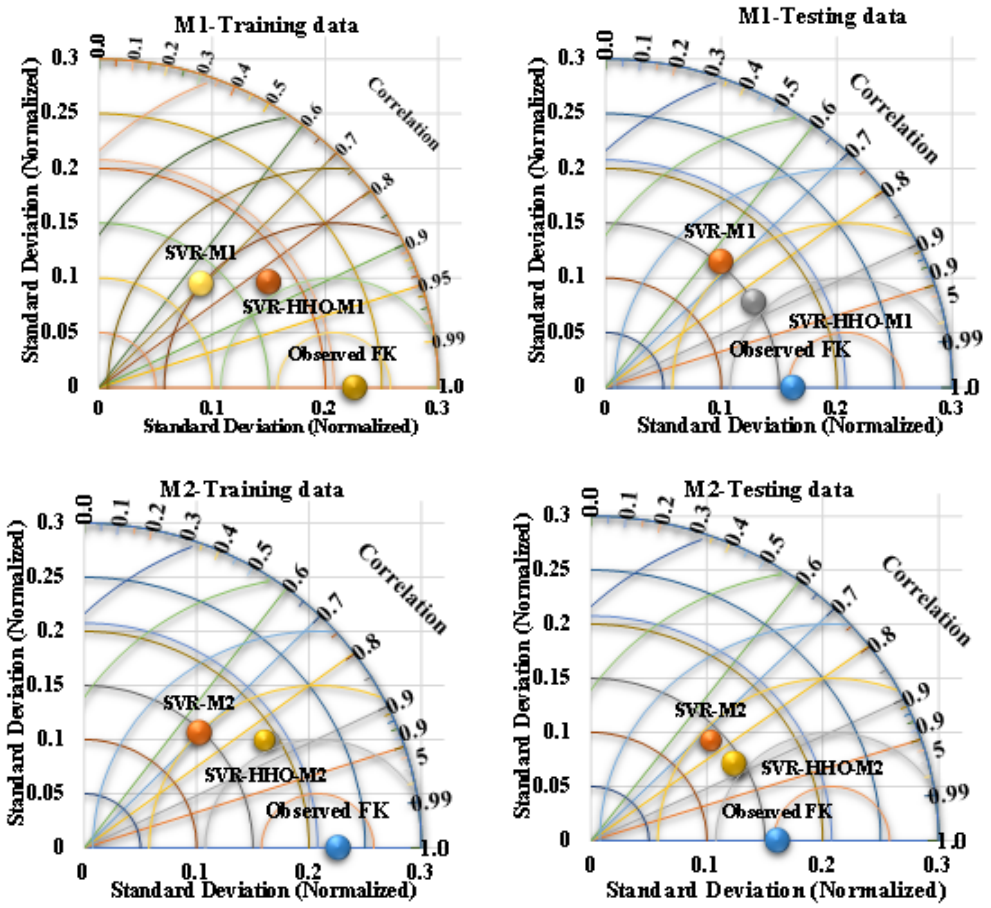


Figure 10*: Taylor graphical representation for M1, and M2 models*

4.0 Conclusion

In this study, two different approaches, including deterministic analysis and data-driven models (ANN, SVM, ANFIS, and MLR) were employed for the evaluation and estimation of knowledge forest among university students in North Cyprus. Subsequently, emerging optimization algorithms called HHO were employed to hybridize SVR model to improve the prediction accuracy of the model. For this purpose, a structured questionnaire was used according to empirical observation, collection, and recording of respondents' opinions, assessment, classification, and interpretation of data through statistical software, with no reason for any biased manipulation of the main objective and scope of the study. The research was piloted among the university students, both at the Undergraduate and Postgraduate levels in North Cyprus to share different experiences about their knowledge and views of the forest resources in their locality. For deterministic analysis, students at all levels of education should strive to have a better understanding of forests, because they have impacted our world in every area financially, ecologically, medically and socio-traditionally. The unique diverse functions of forest endowments are yet to be acknowledged by a great number of nationalities across the globe. Several nations worldwide still place a low priority on forest administration at local, state, and central levels; this has resulted in a low passion for forest care and protection; this also makes forest segments short of improvement, efficiency, and public advocates. Most essentially, probably not every area of vegetation and ecosystem could be known or exposed to all students at the tertiary institution level, while having in mind that their various course of study differs. Although the tertiary institution students have a strong capability for personal learning or learning autonomy, they require sufficient facilities to be provided. Also, the tertiary institutions or higher academic communities ought to take complete liability or task for adequate teaching of forest administration and sustainability; students should be taught on critical thinking about forest, environment, human and socio-economic activities; in all these, they would be

able to query and find out more about origin of forest, forest protection, importance of forest, forest administration, danger of deforestation, and social responsibility regarding forest resources. However, for AI-based models, two different models were developed based on sensitivity analysis to estimate the forest knowledge using ANN, SVM, ANFIS, and MLR models. The performance criteria were evaluated using R2, R, MSE, and RMSE. The predictive results demonstrated that AI-based models are capable of predicting forest knowledge with fewer input combinations. The results further indicated that MLR models are an incapable and unsatisfactory tool for modelling forest knowledge. Among the AI models, SVM-M1 emerges best and hence serves as the most reliable estimation model. The outcomes also suggested that for the development of AI in this field, other nonlinear models and optimization techniques should be employed, such as extreme learning machine, genetic algorithm, and ensemble learning, in order to improve the estimation accuracy.

Competing Interests: The authors declare that they have no competing interests.

Data Availability Statement: The supported data associated with this researcher is available upon request from the corresponding author.

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References

[1] R. Parsons and T. C. Daniel, "Good looking : in defense of scenic landscape aesthetics," vol. 60, pp. 43–56, 2002.
[2] T. Morton, Ecology without nature: Rethinking environmental aesthetics. Harvard University Press, 2007.
[3] B. Reviews, "Ecology without Nature: Rethinking Environmental Aesthetics," pp. 239–240, 2007.
[4] A. I. Journal, S. S. Lim, J. L. Innes, and S. R. J. Sheppard, "Awareness of Aesthetic and Other Forest Values : The Role of Forestry Knowledge and Education Awareness of Aesthetic and Other Forest Values : The Role of Forestry Knowledge and Education," vol. 1920, no. June, 2016, doi: 10.1080/08941920.2015.1041659.
[5] S. Seop, J. L. Innes, and M. Meitner, "Public awareness of aesthetic and other forest values associated with sustainable forest management : A cross-cultural comparison among the public in four countries," J. Environ. Manage., vol. 150, pp. 243–249, 2015, doi: 10.1016/j.jenvman.2014.11.026.
[6] V. Upton, Á. N. Dhubháin, and C. Bullock, "Society & Natural Resources : An Are Forest Attitudes Shaped by the Extent and Characteristics of Forests in the Local Landscape ?," no. February 2015, pp. 37–41, 2014, doi: 10.1080/08941920.2014.933925.
[7] K. Berninger, W. Adamowicz, D. Kneeshaw, and C. Messier, "Sustainable Forest Management Preferences of Interest Groups in Three Regions with Different Levels of Industrial Forestry : An Exploratory Attribute-Based Choice Experiment," pp. 117–133, 2010, doi: 10.1007/s00267-010-9507-1.
[8] E. A. O'Brien, "Publics* and woodlands in England: Well-being, local identity, social learning, conflict and management," Forestry, vol. 78, no. 4, pp. 321–336, 2005, doi: 10.1093/forestry/cpi042.
[9] A. Kostilainena, "A perspective of the students of higher forestry education," For. Sci. Technol., vol. 1, no. 2, pp. 224–227, 2005, doi: 10.1080/21580103.2005.9656291.
[10] S. D. Brody and S. Zahran, "Commentary : Linking particulate matter and sulphur concentrations to air pollution annoyance : problems of measurement , scale and control," pp. 820–823, 2004, doi: 10.1093/ije/dym143.
[11] M. J. Diamantopoulou, "Sustainable Computing : Informatics and Systems Assessing a reliable modeling approach of features of trees through neural network models for sustainable forests," Sustain. Comput. Inform. Syst., vol. 2, no. 4, pp. 190–197, 2012, doi: 10.1016/j.suscom.2012.10.002.
[12] U. J. Frey and H. Rusch, "Using artificial neural networks for the analysis of social-ecological systems," Ecol. Soc., vol. 18, no. 2, 2013, doi: 10.5751/ES-05202-180240.
[13] S. Gopal and C. Woodcock, "Remote sensing of forest change using artificial neural networks," IEEE Trans. Geosci. Remote Sens., vol. 34, no. 2, pp. 398–404, 1996, doi: 10.1109/36.485117.
[14] M. Hanewinkel, S. Hummel, and A. Albrecht, "Assessing natural hazards in forestry for risk management : a review," pp. 329–351, 2011, doi: 10.1007/s10342-010-0392-1.
[15] C. Peng and X. Wen, "Recent Applications of Artificial Neural Networks in Forest Resource Management : An Overview Applications in Forest Resource Management," Am. Assoc. Artif. Intell., 1999.
[16] M. Hanewinkel, W. Zhou, and C. Schill, "A neural network approach to identify forest stands susceptible to wind damage," vol. 196, pp. 227–243, 2004, doi: 10.1016/j.foreco.2004.02.056.
[17] C. Ghent and S. Haines, "An evaluation of ' Forests of the World ', a Project Learning Tree secondary module," Res. High. Educ. J., pp. 1–15, 2013.
[18] D. George and P. Mallery, "SPSS for Windows step by step: A simple guide and reference. 11.0 update," 2003.
[19] C. E. Lance, M. M. Butts, and L. C. Michels, "What Did They Really Say ?," Organ. Res. Methods, vol. 9, no. 2, pp. 202–220, 2006.
[20] S. I. Abba, S. Jasim, and J. Abdullahi, "ScienceDirect ScienceDirect River water modelling prediction using multi-linear regression , artificial neural network , and adaptive neuro-fuzzy inference system techniques," Procedia Comput. Sci., vol. 120, pp. 75–82, 2018, doi: 10.1016/j.procs.2017.11.212.

[21] S. Tayyebi, Z. Hajjar, and S. Soltanali, "A novel modified training of radial basis network: Prediction of conversion and selectivity in 1-hexene dimerization process," Chemom. Intell. Lab. Syst., vol. 190, no. May, pp. 1–9, 2019, doi: 10.1016/j.chemolab.2019.05.005.
[22] G. Elkiran, V. Nourani, S. I. Abba, and J. Abdullahi, "Artificial intelligence-based approaches for multi-station modelling of dissolve oxygen in river," Glob. J. Environ. Sci. Manag., vol. 4, no. 4, pp. 439–450, 2018, doi: 10.22034/gjesm.2018.04.005.
[23] V. Nourani, G. Elkiran, and J. Abdullahi, "Multi-station artificial intelligence based ensemble modeling of reference evapotranspiration using pan evaporation measurements," J. Hydrol., vol. 577, no. March, p. 123958, 2019, doi: 10.1016/j.jhydrol.2019.123958.
[24] V. Nourani, G. Elkiran, and S. I. Abba, "Wastewater treatment plant performance analysis using artificial intelligence – an ensemble approach," Water Sci. Technol., 2018, doi: 10.2166/wst.2018.477.
[25] H. Sanikhani and O. Kisi, "River Flow Estimation and Forecasting by Using Two Different Adaptive Neuro-Fuzzy Approaches," Water Resour. Manag., vol. 26, no. 6, pp. 1715–1729, 2012, doi: 10.1007/s11269-012-9982-7.
[26] W. Kristjanpoller and M. C. Minutolo, "Forecasting volatility of oil price using an artificial neural network-GARCH model," Expert Syst. Appl., vol. 65, pp. 233–241, 2016, doi: 10.1016/j.eswa.2016.08.045.
[27] Z. M. Yaseen et al., "Rainfall Pattern Forecasting Using Novel Hybrid Intelligent Model Based ANFIS-FFA," Water Resour. Manag., vol. 32, no. 1, pp. 105–122, 2018, doi: 10.1007/s11269-017-1797-0.
[28] S.-S. Sharifi, R. Delirhasannia, V. Nourani, A. Sadraddini, and A. Ghorbani, "Using Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference System (ANFIS) for Modeling and Sensitivity Analysis of Effective Rainfall," Recent Adv. Contin. Mech. Hydrol. Ecol., no. June, pp. 133–139, 2013.
[29] P. Kumar, K. V. Kendra, and L. Gramvidhyapith, "DAILY RAINFALL FORECASTING USING ADAPTIVE NEURO- FUZZY INFERENCE SYSTEM (Anfis) MODELS," vol. 6, no. 3, pp. 382–388, 2015.
[30] S. A. Akrami, V. Nourani, and S. J. S. Hakim, "Development of Nonlinear Model Based on Wavelet-ANFIS for Rainfall Forecasting at Klang Gates Dam," Water Resour. Manag., vol. 28, no. 10, pp. 2999–3018, 2014, doi: 10.1007/s11269-014-0651-x.
[31] Q. B. Pham et al., "Potential of Hybrid Data-Intelligence Algorithms for Multi-Station Modelling of Rainfall," Water Resour. Manag., 2019, doi: 10.1007/s11269-019-02408-3.
[32] S. I. Abba, A. Saleh, N. Hamza, A. I. Tukur, and N. A. Wahab, "Modelling of Uncertain System : A comparison study of Linear and Non-Linear Approaches," IEEE, 2019.
[33] F. Khademi, K. Behfarnia, and S. Engineering, "EVALUATION OF CONCRETE COMPRESSIVE STRENGTH c r v i h o e f c f," vol. 6, no. 3, pp. 423–432, 2016.
[34] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, "Harris hawks optimization: Algorithm and applications," Future Gener. Comput. Syst., vol. 97, no. March, pp. 849–872, 2019, doi: 10.1016/j.future.2019.02.028.
[35] H. Moayedi, M. Gör, Z. Lyu, and D. T. Bui, "Herding Behaviors of grasshopper and Harris hawk for hybridizing the neural network in predicting the soil compression coefficient," Measurement, vol. 152, p. 107389, Feb. 2020, doi: 10.1016/j.measurement.2019.107389.
[36] H. Moayedi et al., "Harris hawks optimization: A novel swarm intelligence technique for spatial assessment of landslide susceptibility," Sens. Switz., 2019, doi: 10.3390/s19163590.
[37] A. Malik, "Prediction of meteorological drought by using hybrid support vector regression optimized with HHO versus PSO algorithms," 2021.
[38] H. Moayedi, A. Osouli, H. Nguyen, and A. S. A. Rashid, "A novel Harris hawks' optimization and k-fold cross-validation predicting slope stability," Eng. Comput., 2019, doi: 10.1007/s00366-019-00828-8.
[39] M. Z. Islam et al., "A Harris Hawks optimization based singleand multi-objective optimal power flow considering environmental emission," Sustain. Switz., vol. 12, no. 13, 2020, doi: 10.3390/su12135248.
[40] J. Yu, C. H. Kim, and S. B. Rhee, "The Comparison of Lately Proposed Harris Hawks Optimization and Jaya Optimization in Solving Directional Overcurrent Relays Coordination Problem," Complexity, vol. 2020, no. iii, 2020, doi: 10.1155/2020/3807653.
[41] S. J. Hadi, S. I. Abba, S. Sh. Sammen, S. Q. Salih, N. Al-Ansari, and Z. M. Yaseen, "Non-Linear Input Variable Selection Approach Integrated With Non-Tuned Data Intelligence Model for Streamflow Pattern Simulation," IEEE Access, vol. 7, pp. 141533–141548, 2019, doi: 10.1109/access.2019.2943515.
[42] G. J. M. David R Legates, "Evaluating the use of “goodness-of-fit” Measures in hydrologic and hydroclimatic model validation," vol. 35, no. 1, pp. 1–9, 2007.
[43] S. S. Lim, J. L. Innes, and S. R. J. Sheppard, "Awareness of Aesthetic and Other Forest Values: The Role of Forestry Knowledge and Education," Soc. Nat. Resour., vol. 28, no. 12, pp. 1308–1322, 2015, doi: 10.1080/08941920.2015.1041659.
[44] A. E. S. III, Psychology and the aesthetics of the built environment. Springer Science & Business Media, 2013.
[45] A. E. Stamps, "Demographic effects in environmental aesthetics: A meta-analysis," J. Plan. Lit., vol. 14, no. 2, pp. 155–175, 1999, doi: 10.1177/08854129922092630.
[46] J. Arevalo, S. Pitkänen, and B. Kirongo, "Developing forestry curricula: Experiences from a kenyan-finnish project," Int. For. Rev., vol. 16, no. 1, pp. 78–86, 2014, doi: 10.1505/146554814811031242.
[47] J. C. Gordon, "Forestry education and research in the United States: A story of shifting paradigms," For. Sci. Technol., vol. 2, no. 2, pp. 111–122, 2006, doi: 10.1080/21580103.2006.9656306.
[48] J. Parrotta, Y. Yeo-Chang, and L. D. Camacho, "Traditional knowledge for sustainable forest management and provision of ecosystem services," Int. J. Biodivers. Sci. Ecosyst. Serv. Manag., vol. 12, no. 1–2, pp. 1–4, 2016, doi: 10.1080/21513732.2016.1169580.
[49] O. Segura-Bonilla, "Competitiveness, systems of innovation and the learning economy: The forest sector in Costa Rica," For. Policy Econ., vol. 5, no. 4, pp. 373–384, 2003, doi: 10.1016/S1389-9341(03)00036-4.

[50] W. D. Sunderlin et al., "Livelihoods, forests, and conservation in developing countries: An overview," World Dev., vol. 33, no. 9 SPEC. ISS., pp. 1383–1402, 2005, doi: 10.1016/j.worlddev.2004.10.004.
[51] M. Bonera, E. Corvi, A. P. Codini, and R. Ma, "Does Nationality Matter in Eco-Behaviour ?," pp. 1–17, 2017, doi: 10.3390/su9101694.
[52] C. Li, C. P. Wang, S. T. Liu, and L. H. Weng, "Forest value orientations and importance of forest recreation services," J. Environ. Manage., vol. 91, no. 11, pp. 2342–2348, 2010, doi: 10.1016/j.jenvman.2010.06.020.
[53] G. Weiss et al., "Forest ownership changes in Europe: State of knowledge and conceptual foundations," For. Policy Econ., vol. 99, no. March 2018, pp. 9–20, 2019, doi: 10.1016/j.forpol.2018.03.003.
[54] P. W. Chirwa, L. Mahamane, and G. Kowero, "Forests, people and environment: some African perspectives§," South. For., vol. 79, no. 2, pp. 79–85, 2017, doi: 10.2989/20702620.2017.1295347.
[55] I. O. Azeez, L. Popoola, and I. O. Shulamite, "An assessment of the forest regeneration potential of the taungya system of farming in Oyo," vol. 2620, 2017, doi: 10.2989/20702620.2016.1255425.
[56] I. Nhantumbo and M. Camargo, REDD+ for profit or for good? Review of private sector and NGO experience in REDD+ projects. 2015.
[57] M. A. Carbonero, L. J. Martín-antón, L. Otero, E. Monsalvo, and J. L. Castejon, "Program to Promote Personal and Social Responsibility in the Secondary Classroom," vol. 8, no. May, pp. 1–12, 2017, doi: 10.3389/fpsyg.2017.00809.
[58] C. Dlamini, M. Larwanou, and P. W. Chirwa, "A brief overview of the capacities of public forest administrations in climate change work in the moist forests countries of Sub-Saharan Africa," Int. For. Rev., vol. 17, no. 3, pp. 53–66, 2015, doi: 10.1505/146554815816007036.
[59] X. Ji, X. Shang, R. A. Dahlgren, and M. Zhang, "Prediction of dissolved oxygen concentration in hypoxic river systems using support vector machine: a case study of Wen-Rui Tang River, China," Environ. Sci. Pollut. Res., vol. 24, no. 19, pp. 16062–16076, 2017, doi: 10.1007/s11356-017-9243-7.
[60] E. Olyaie, H. Zare Abyaneh, and A. Danandeh Mehr, "A comparative analysis among computational intelligence techniques for dissolved oxygen prediction in Delaware River," Geosci. Front., vol. 8, no. 3, pp. 517–527, 2017, doi: 10.1016/j.gsf.2016.04.007.
[61] R. Eisinga, M. Te Grotenhuis, and B. Pelzer, "The reliability of a two-item scale: Pearson, Cronbach, or Spearman-Brown?," Int. J. Public Health, vol. 58, no. 4, pp. 637–642, 2013, doi: 10.1007/s00038-012-0416-3.
[62] Z. M. Yaseen, S. O. Sulaiman, R. C. Deo, and K. W. Chau, "An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction," J. Hydrol., vol. 569, no. October 2018, pp. 387–408, 2019, doi: 10.1016/j.jhydrol.2018.11.069.
[63] M. Hameed, S. S. Sharqi, Z. M. Yaseen, H. A. Afan, A. Hussain, and A. Elshafie, "Application of artificial intelligence (AI) techniques in water quality index prediction: a case study in tropical region, Malaysia," Neural Comput. Appl., vol. 28, pp. 893–905, 2017, doi: 10.1007/s00521-016-2404-7.
[64] M. A. Ghorbani, R. C. Deo, Z. M. Yaseen, M. H. Kashani, and B. Mohammadi, "Pan evaporation prediction using a hybrid multilayer perceptron-firefly algorithm (MLP-FFA) model: case study in North Iran," Theor. Appl. Climatol., vol. 133, no. 3–4, pp. 1119–1131, 2018, doi: 10.1007/s00704-017-2244-0.
[65] Z. M. Yaseen et al., "A novel hybrid evolutionary data-intelligence algorithm for irrigation and power production management: Application to multi-purpose reservoir systems," Sustain. Switz., vol. 11, no. 7, 2019, doi: 10.3390/su11071953.
[66] S. I. Abba et al., "Emerging evolutionary algorithm integrated with kernel principal component analysis for modeling the performance of a water treatment plant," J. Water Process Eng., vol. 33, no. December 2019, p. 101081, 2020, doi: 10.1016/j.jwpe.2019.101081.
[67] S. I. Abba, V. Nourani, and G. Elkiran, "Multi-parametric modeling of water treatment plant using AI-based non-linear ensemble," J. Water Supply Res. Technol.-Aqua, vol. 68, no. 7, pp. 547–561, 2019.
[68] J. ; Hair, W. ; Black, B. ; Babin, and R. Anderson, Multivariate Data Analysis, 7th ed. Upper Saddle River, NJ, USA.: Prentice-Hall, Inc., 2010.
[69] S. I. Abba et al., "Hybrid machine learning ensemble techniques for modeling dissolved oxygen concentration," IEEE Access, vol. 8, no. September, pp. 157218–157237, 2020, doi: 10.1109/ACCESS.2020.3017743.
[70] D. A. Dickey, W. A. Fuller, D. A. Dickey, and W. A. Fuller, "Journal of the American Statistical Association Distribution of the Estimators for Autoregressive Time Series with a Unit Root Distribution of the Estimators for Autoregressive Time Series With a Unit Root," Taylor Publ., no. July 2015, pp. 37–41, 2012, doi: 10.1080/01621459.1979.10482531.
[71] C. J. Willmott and K. Matsuura, "Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance," Clim. Res., vol. 30, no. 1, pp. 79–82, 2005, doi: 10.3354/cr030079.
[72] M. A. Ghorbani, R. C. Deo, Z. M. Yaseen, M. H. Kashani, and B. Mohammadi, "Pan evaporation prediction using a hybrid multilayer perceptron-firefly algorithm (MLP-FFA) model: case study in North Iran," Theor. Appl. Climatol., vol. 133, no. 3–4, pp. 1119–1131, 2018, doi: 10.1007/s00704-017-2244-0.
[73] K. E. Taylor, "Summarizing multiple aspects of model performance in a single diagram," J. Geophys. Res., vol. 106, no. D7, pp. 7183–7192, 2001, doi: 10.1029/2000JD900719.