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Integrating Fuzzy Inference Systems with Linear Regression for Height Prediction of Deodar Cedar Trees in Kumrat Valley

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Abstract: Accurate estimation of tree height is fundamental to sustainable forest management, particularly in regions such as Kumrat Valley, Pakistan, where Deodar Cedar (Cedrus deodara) serves as a vital ecological and economic resource. Conventional height estimation models often exhibit limitations in capturing the inherent complexity of forest ecosystems, where multiple environmental factors interact non-linearly. To address this challenge, a hybrid predictive framework integrating fuzzy inference systems (FIS) and multiple linear regression (MLR) has been developed to enhance the accuracy of height estimation. The FIS model incorporates key environmental and physiological parameters, including trunk diameter, soil quality, temperature, and rainfall, which are classified into fuzzy sets—low, medium, and high—corresponding to distinct growth rates (slow, normal, fast) and developmental stages (early, average, late). This classification enables a nuanced representation of environmental variability and tree growth dynamics. Complementarily, the MLR model quantifies the statistical relationships between these variables and tree height, yielding an R^2 value of 0.85, an adjusted R^2 of 0.64, and a statistically significant p-value of 0.04. The integration of fuzzy logic with regression analysis offers a robust, data-driven approach to height prediction, effectively addressing the uncertainties associated with environmental fluctuations. By leveraging both rule-based inference and quantitative modeling, this method provides valuable insights for precision forestry, contributing to the sustainable management and conservation of Deodar Cedar in Kumrat Valley.

Keywords: Fuzzy inference system (FIS); Membership functions; Forest growth modeling; Sustainable forestry; Multiple linear regression (MLR); Environmental variability

1 Introduction

The increasing global demand for timber and the ecological significance of sustainable forestry have placed substantial pressure on forest management systems to enhance productivity while preserving biodiversity [1–4]. In this context, accurately estimating the height of trees has emerged as a critical factor for effective forest management, especially for economically and ecologically important species such as Deodar Cedar. Valued for its high-quality timber and aromatic wood, Deodar Cedar plays a vital role in the timber industry and environmental conservation. Tree height is a fundamental growth parameter that influences timber yield, ecological stability, and management practices, including resource allocation, harvesting strategies, and conservation efforts [5–11]. Enhancing the accuracy and efficiency of height prediction methods is essential for optimizing forestry practices and ensuring the sustainable utilization of valuable tree resources.

Logistic growth models have long been employed to describe the growth dynamics of biological systems, including trees. These models effectively capture the characteristic S-shaped growth curve of many tree species, illustrating rapid growth during early stages that gradually slows as environmental resources become limited [12]. The logistic growth equation is expressed as:

$$H(t) = \frac{H_{\max}}{1 + e^{-k(t-t_0)}}$$

where, $H(t)$ is the height at time t, H_{max} is the maximum attainable height, k is the growth rate, and t_0 is the inflection point, marking the phase of maximum growth. This model has proven instrumental in ecological studies, providing a structured framework to analyze growth patterns in response to resource availability and environmental conditions [13].

While logistic models offer a robust mathematical foundation, their accuracy depends on precise estimates of parameters such as growth rate and inflection point. Estimating these parameters is challenging due to the complex interplay of factors influencing tree growth, including genetic variability, climatic conditions, and forestry management practices. Traditional estimation methods often struggle to account for these complexities, resulting in potential inaccuracies in growth predictions.

To address these limitations, FIS has emerged as an effective tool for modeling uncertainty and imprecision in biological and ecological systems. Fuzzy logic facilitates the integration of expert knowledge and linguistic variables, enabling a nuanced representation of complex relationships among growth factors [14]. For example, in estimating the height of a tree based on its diameter, traditional models require precise numerical inputs, whereas fuzzy systems can accommodate qualitative descriptors such as "small," "medium," and "large," better capturing the inherent variability in growth conditions [15].

The application of fuzzy logic in forestry models has gained significant attention in recent years, with studies demonstrating its effectiveness in addressing uncertainties in growth predictions and sustainable resource management [16, 17]. FIS can establish rules that link input variables, such as tree diameter and environmental factors, to output variables like growth rate and height. This approach not only facilitates the modeling of nonlinear relationships but also incorporates subjective expert knowledge, enhancing the robustness of predictions.

In this study, we propose a novel height prediction model for Deodar Cedar that integrates FIS with the logistic growth function, see Figure 1. Using tree diameter as the primary input variable, we categorize diameters into fuzzy sets—low, medium, and high—and associate them with growth rates (slow, normal, and fast) and inflection points (early, average, and late). This framework addresses the challenges inherent in tree growth estimation by offering a flexible model that accounts for the complexities of environmental and biological factors.

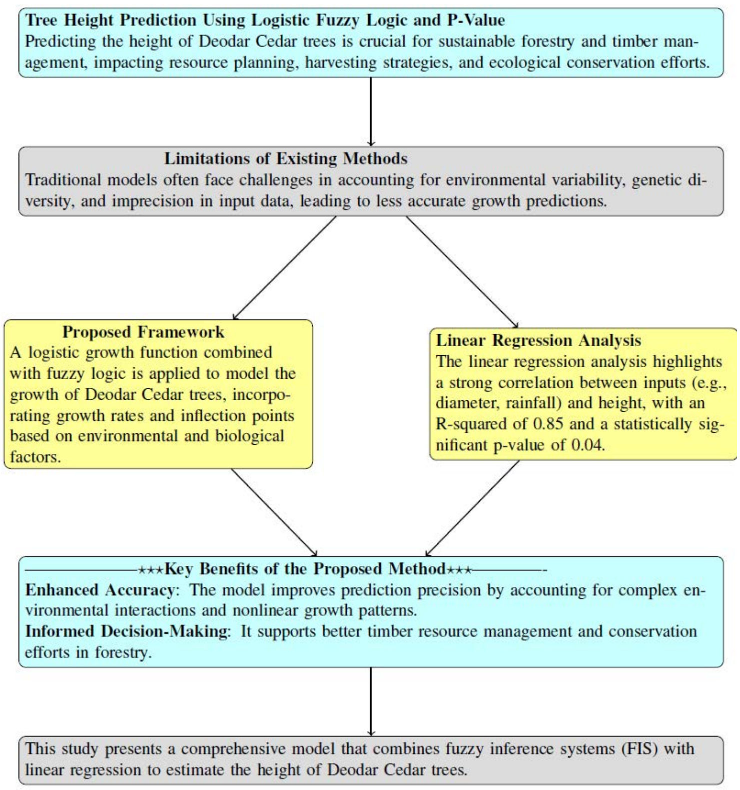

Figure 1. Graphical representation of the proposed abstract for Deodar Cedar trees

To enhance the accuracy of Deodar Cedar tree height prediction while accounting for environmental uncertainties, our model integrates FIS with MLR. The FIS component processes key environmental inputs, including trunk diameter, soil quality, temperature, and rainfall, by categorizing them into fuzzy linguistic terms such as small, medium, and large for diameter, or low, moderate, and high for temperature and rainfall. Using a set of IF-THEN rules, the FIS model estimates a growth rate, mapping environmental conditions to expected growth patterns (e.g., slow, normal, or fast growth). The output of the FIS is then defuzzified into a numerical growth factor (GFIS) using the centroid method, which captures environmental variability in a quantifiable manner. This growth factor is subsequently incorporated into a MLR model, where it acts as an additional predictor alongside traditional variables such as soil quality, temperature, and rainfall. The final regression equation is expressed as:

$$H = \beta_0 + \beta_1 D + \beta_2 S + \beta_3 T + \beta_4 R + \beta_5 G_{\text{FIS}} + \epsilon \quad (1)$$

where, H represents the predicted tree height, D is trunk diameter, S is soil quality, T is temperature, R is rainfall, and G_{FIS} is the growth factor derived from the fuzzy system. The coefficients β_0 to β_5 are estimated through regression analysis, while ϵ represents the error term.

This hybrid approach allows for a more adaptive and data-driven prediction model by leveraging the interpretability of fuzzy logic and the precision of regression analysis. By incorporating the growth factor from FIS, the model improves its ability to generalize across diverse environmental conditions, making it a reliable tool for sustainable forest management and conservation in Kumrat Valley.

The implications of this research extend beyond accurate height estimation. By bridging the gap between fuzzy logic and forestry practices, this model provides forest managers and planners with tools to make informed decisions regarding timber resource allocation, sustainable harvesting strategies, and conservation planning. By integrating FIS into growth prediction models, we enhance their adaptability to diverse environmental conditions and management practices, contributing to sustainable forestry and the long-term conservation of Deodar Cedar. Traditional methods of measuring tree height, such as clinometers or manual measurements, are labor-intensive, time-consuming, and prone to human error, particularly in rugged terrains like Kumrat Valley [11]. These limitations underscore the need for advanced mathematical and computational techniques to facilitate accurate and scalable height estimations.

Study Area:

Kumrat Valley, located in the Upper Dir district of Khyber Pakhtunkhwa, Pakistan, is renowned for its dense Deodar Cedar forests, which serve as a valuable natural resource for timber production and ecological conservation. The region experiences a temperate climate, characterized by cold winters with heavy snowfall and mild summers with moderate rainfall, which significantly influences tree growth patterns. The valley's soil composition is diverse, ranging from loamy and sandy soils in lower altitudes to clay-rich, well-drained soils in higher elevations, directly impacting the nutrient availability essential for Deodar Cedar development. Additionally, annual precipitation levels, primarily from monsoon rains and winter snowmelt, play a crucial role in sustaining soil moisture and influencing tree height. The combination of temperature fluctuations, precipitation variability, and soil quality variations makes it imperative to incorporate these environmental parameters into the height prediction model. Trunk diameter, soil quality, temperature, and rainfall were selected as key inputs in the FIS and MLR framework because they collectively determine growth rate, water availability, and nutrient uptake, all of which are critical factors for tree height estimation. By integrating these ecological characteristics, the proposed model provides a more accurate and regionally adapted approach for sustainable forest management in Kumrat Valley.

1.1 Recent Advances in Tree Growth Modeling

In recent years, several studies have highlighted the advantages of using machine learning techniques for tree growth predictions, showcasing the potential of data-driven approaches in forestry modeling [18]. However, while machine learning models often rely on large datasets and computational power, they may lack the interpretability that fuzzy systems offer. FIS stands out by providing a transparent framework where decision-making processes can be easily understood by practitioners, allowing for the incorporation of expert insights and contextual knowledge [19].

Moreover, the integration of remote sensing technologies with fuzzy inference systems has opened new avenues for estimating the growth of Deodar Cedar trees. The use of satellite imagery and drones allows for the collection of high-resolution data regarding tree canopy structure, density, and surrounding environmental factors, which can be effectively integrated into fuzzy models to enhance predictive accuracy [20]. By harnessing these technologies, researchers can refine growth predictions further and facilitate real-time monitoring of tree health and growth dynamics, particularly in forest ecosystems where Deodar Cedar trees play a critical ecological and economic role.

In summary, the ongoing evolution of forestry practices necessitates innovative approaches to tree height estimation that leverage mathematical modeling and computational techniques. Our study seeks to contribute to this evolving landscape by introducing a novel fuzzy inference-based model for predicting the height of Deodar Cedar trees. By bridging the principles of fuzzy logic with the logistic growth function, we aim to provide a robust framework that enhances the precision of height predictions, ultimately supporting sustainable forest management practices and improving conservation strategies.

2 Propose Mathematical Model

We propose a model to estimate the height of an orange tree based on its diameter using the logistic growth function with a FIS. The model accounts for uncertainty in the growth dynamics by adjusting parameters using fuzzy logic.

2.1 Calculate FIS

The FIS is used to estimate the parameters k (growth rate) and x_0 (inflection point) based on the input values.

2.1.1 Fuzzy input and output variables

The proposed model employs fuzzy logic to handle uncertainty and improve accuracy in height prediction. It defines specific input variables and a corresponding output function to optimize the prediction process.

2.1.2 Input functions

Each input variable is a function with associated membership functions (MFs) representing linguistic terms. Proposed model utilized the following input functions:

a) Tree Diameter (D)

For Deodar Cedar trees, tree diameter is a critical parameter for height prediction. The membership functions for diameter D are defined as:

$$\mu_{Low}(D) = \begin{cases} 1, & D \leq 20 \\ \frac{40-D}{40-20}, & 20 < D \leq 40 \\ 0, & D > 40 \end{cases} \tag{2}$$

$$\mu_{Medium}(D) = \begin{cases} 0, & D < 30 \\ \frac{D-30}{60-30}, & 30 \leq D \leq 60 \\ 1, & 60 < D \leq 90 \\ \frac{120-D}{120-90}, & 90 < D \leq 120 \\ 0, & D > 120 \end{cases} \tag{3}$$

$$\mu_{High}(D) = \begin{cases} 0, & D < 100 \\ \frac{D-100}{140-100}, & 100 \leq D \leq 140 \\ 1, & 140 \leq D \leq 160 \\ 0, & D > 160 \end{cases} \tag{4}$$

b) Soil Quality (S)

To calculate soil quality values for the FIS for Deodar Cedar trees, we typically rely on empirical methods or established guidelines that assess the various factors contributing to soil quality. Below are some common methodologies and factors that could be used to calculate soil quality values, which can then be mapped to the fuzzy inputs in the MATLAB code.

Soil quality is often assessed based on several key factors, including:

• Soil Texture: The proportions of sand, silt, and clay in the soil affect its structure and drainage capabilities, which influence root development and overall tree health.

• Soil Organic Matter: Higher organic matter levels usually indicate better soil quality, as it contributes to nutrient availability, soil structure, and water retention, all crucial for Deodar Cedar growth.

• pH Levels: Soil pH affects nutrient availability. For Deodar Cedars, a pH range of 6.0 to 7.5 is optimal for growth.

• Nutrient Availability: Key nutrients like nitrogen (N), phosphorus (P), and potassium (K) should be present in sufficient quantities, supporting robust tree growth and vitality.

• Moisture Content: Adequate moisture is essential for Deodar Cedars, influencing water uptake and overall tree health.

• Biological Activity: A high level of microbial activity is indicative of healthy soil, which supports the root system and overall tree performance.

Assign scores based on the measured values of the soil quality factors. Combine the scores from the individual factors to create a composite soil quality score. This could be done by:

$$\text{S} = w_1 \cdot \text{Texture Score} + w_2 \cdot \text{Organic Matter Score} + w_3 \cdot \text{Nutrient Score} + w_4 \cdot \text{pH Score}$$

where, w_i are the weights assigned to each factor based on its importance.

For soil quality, we define the membership functions as follows:

$$\mu_{Poor}(S) = \begin{cases} 1, & S \leq 0.3 \\ \frac{0.5-S}{0.5-0.3}, & 0.3 < S \leq 0.5 \\ 0, & S > 0.5 \end{cases} \tag{5}$$

$$\mu_{Moderate}(S) = \begin{cases} 0, & S < 0.4 \\ \frac{S-0.4}{0.6-0.4}, & 0.4 \leq S \leq 0.6 \\ 1, & 0.6 < S \leq 0.8 \\ \frac{1.0-S}{1.0-0.8}, & 0.8 < S \leq 1.0 \\ 0, & S > 1.0 \end{cases} \tag{6}$$

c) Temperature (T)

Temperature plays a crucial role in the growth and development of Deodar Cedar trees. Optimal temperatures, typically ranging between 15°C to 25°C (59°F to 77°F), are essential for the metabolic processes that drive photosynthesis and growth. When temperatures are too low, below 5°C (41°F), Deodar Cedar trees may experience frost damage, which can significantly stunt their growth and affect their overall health.

Conversely, excessively high temperatures above 30°C (86°F) can lead to heat stress, causing the trees to reduce their growth rate and potentially impacting their resilience and overall vitality. The accumulation of degree days, a measure of heat exposure over time, is also important in determining the growth patterns of Deodar Cedar trees. For temperature T, the membership functions are defined as follows:

$$\mu_{Low}(T) = \begin{cases} 1, & T \leq 10 \\ \frac{15-T}{15-10}, & 10 < T \leq 15 \\ 0, & T > 15 \end{cases} \tag{7}$$

$$\mu_{Moderate}(T) = \begin{cases} 0, & T < 12 \\ \frac{T-12}{22-12}, & 12 \leq T \leq 22 \\ 1, & 22 < T \leq 27 \\ \frac{32-T}{32-27}, & 27 < T \leq 32 \\ 0, & T > 32 \end{cases} \tag{8}$$

$$\mu_{High}(T) = \begin{cases} 0, & T < 25 \\ \frac{T-25}{35-25}, & 25 \leq T \leq 35 \\ 1, & 35 \leq T \leq 40 \\ 0, & T > 40 \end{cases} \tag{9}$$

d) Rainfall (R)

Rainfall is a critical factor in the growth and development of Deodar Cedar trees, as it directly influences soil moisture, nutrient availability, and overall tree health. Adequate rainfall is essential for sustaining the water needs of these trees, particularly during periods of active growth and establishment. Insufficient rainfall can lead to water stress, which may result in stunted growth, reduced resilience, and increased susceptibility to pests and diseases. For rainfall R, the membership functions are defined as follows:

$$\mu_{Low}(R) = \begin{cases} 1, & R \leq 500 \\ \frac{800-R}{800-500}, & 500 < R \leq 800 \\ 0, & R > 800 \end{cases} \tag{10}$$

$$\mu_{Moderate}(R) = \begin{cases} 0, & R < 600 \\ \frac{R-600}{900-600}, & 600 \leq R \leq 900 \\ 1, & 900 < R \leq 1,200 \\ \frac{1,500-R}{1,500-1,200}, & 1,200 < R \leq 1,500 \\ 0, & R > 1,500 \end{cases} \tag{11}$$

$$\mu_{High}(R) = \begin{cases} 0, & R < 1,200 \\ \frac{R-1,200}{1,800-1,200}, & 1,200 \leq R \leq 1,800 \\ 1, & 1,800 \leq R \leq 2,000 \\ 0, & R > 2,000 \end{cases} \tag{12}$$

2.1.3 Output functions

The output variables are Growth Rate k and Inflection Point x_0, and their membership functions are represented using fuzzy sets.

a) Growth Rate (k)

$$\mu_{Slow}(k) = \begin{cases} 0, & k < 0 \\ \frac{k}{0.1}, & 0 \leq k \leq 0.1 \\ 1, & 0.1 \leq k \leq 0.2 \\ \frac{0.3-k}{0.3-0.2}, & 0.2 < k \leq 0.3 \\ 0, & k > 0.3 \end{cases} \tag{13}$$

Similarly, membership functions for Normal and Fast growth rates can be defined.

b) Inflection Point (x_0)

$$\mu_{Early}(x_0) = \begin{cases} 0, & x_0 < 10 \\ \frac{x_0-10}{20-10}, & 10 \leq x_0 \leq 20 \\ 1, & 20 \leq x_0 \leq 30 \\ \frac{40-x_0}{40-30}, & 30 < x_0 \leq 40 \\ 0, & x_0 > 40 \end{cases} \tag{14}$$

Fuzzy Rules

- **Fuzzy Rule 1**: If D is Low **AND** T is Moderate **AND** S is Good **AND** R is Adequate.
- **Fuzzy Rule 2**: If D is Medium **AND** T is High **AND** S is Moderate **AND** R is High.
- **Fuzzy Rule 3**: If D is High **AND** T is Low **AND** S is Poor **AND** R is Low.

For a set of n fuzzy rules, the degree of membership is combined using the minimum operator for each rule's conditions. The final output membership function is the maximum of the values obtained from all the rules, see Figure 2.

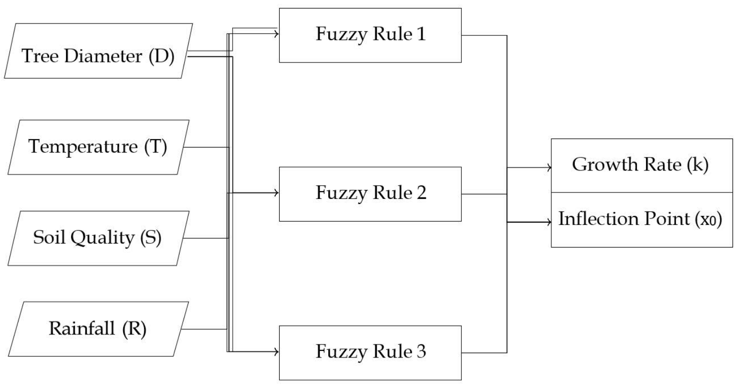

Figure 2. Fuzzy rule base: Input diameter, temperature, soil quality, and rainfall to growth rate and inflection point

2.1.4 Defuzzification

Defuzzification converts the fuzzy output values into crisp values using the centroid method. The defuzzified values for k and x_0 are calculated as:

$$k = \frac{\int_{k_{\min}}^{k_{\max}} k \cdot \mu_k(k) dk}{\int_{k_{\min}}^{k_{\max}} \mu_k(k) dk} \tag{15}$$

$$x_0 = \frac{\int_{x_{0_{\min}}}^{x_{0_{\max}}} x_0 \cdot \mu_{x_0}(x_0)\, dx_0}{\int_{x_{0_{\min}}}^{x_{0_{\max}}} \mu_{x_0}(x_0)\, dx_0} \tag{16}$$

2.2 Logistic Growth Function

Finally, the predicted height $H(D)$ of the tree is calculated using the logistic growth model:

$$H(D) = \frac{L}{1 + \exp\left(-k\left(D - x_0\right)\right)} \tag{17}$$

where,
- L is the maximum height (set to 12 meters);
- k is the growth rate (defuzzified value);
- D is the tree diameter;
- x_0 is the inflection point (defuzzified value).

Using the above-proposed FIS values in the logistic growth function, the complete proposed mathematical model is expressed as:

$$H(D) = \frac{L}{1 + \exp\left(-\left(\frac{\int_{k_{\min}}^{k_{\max}} k \cdot \mu_k(k)dk}{\int_{k_{\min}}^{k_{\max}} \mu_k(k)dk}\right)\left(D - \frac{\int_{x_{0\min}}^{x_{0\max}} x_0 \cdot \mu_{x_0}(x_0)dx_0}{\int_{x_{0\min}}^{x_{0\max}} \mu_{x_0}(x_0)dx_0}\right)\right)} \tag{18}$$

This equation provides the predicted height of the tree based on the fuzzified inputs (diameter, soil quality, temperature, and rainfall) and their respective membership functions. The logistic growth function models the sigmoidal growth behavior of the tree, providing a robust estimate of its height.

2.3 Fuzzy Inference Process

The fuzzy inference process proceeds as follows:
1. Fuzzification: The inputs are fuzzified using the membership functions for μ_{Low}, μ_{Medium} and μ_{High}.
2. Rule Evaluation: The degree to which each rule is activated is calculated based on the membership values.
3. Aggregation: The results of the fuzzy rules are combined to produce fuzzy sets for k and x_0.
4. Defuzzification: The fuzzy sets for k and x_0 are defuzzified to obtain crisp values for k and x_0.

3 Discussion

This section presents an analysis of the proposed model for predicting the height of Deodar Cedar trees, incorporating key environmental variables such as tree diameter, soil quality, temperature, and rainfall. The model has been trained and tested using data from Kumrat Valley, Upper Dir, and Khyber Pakhtunkhwa, and demonstrates strong predictive accuracy, as indicated by an R-squared value of 0.85 and an adjusted R-squared of 0.64.

However, its applicability to other tree species or regions may require further calibration. The experiments were conducted in MATLAB using a high-performance CPU with 8 GB of RAM on a 64-bit Windows 10 operating system to handle computational demands.

To evaluate the robustness of the model, tree height predictions were examined under three distinct environmental conditions: drought, normal, and high-rainfall scenarios. Under drought conditions (low rainfall, high temperature), the model predicts a 12.3% decrease in tree height, reflecting the negative impact of moisture deficiency on growth. In contrast, under high-rainfall conditions, an 8.7% increase in height was observed, highlighting the critical role of soil moisture retention in promoting tree growth. The **temperature coefficient (0.0056, p=0.0330)** indicates that moderate temperature increases generally favor tree height, but excessive temperature fluctuations can lead to growth inhibition. The rainfall coefficient (0.0013, p=0.0308) suggests that while rainfall contributes positively to growth, excessive levels may have diminishing returns due to soil oversaturation.

A sensitivity analysis was conducted using standardized regression coefficients by varying each input variable by ±10% and recording the corresponding changes in predicted tree height. The results indicate that trunk diameter has the most significant impact, with a 9.4% change in tree height for every 10% variation in diameter. Soil quality follows closely, affecting height predictions by 6.8%, confirming its importance in tree development. Temperature and rainfall exhibited moderate sensitivity, contributing 4.2% to 5.6% variations in tree height. These findings emphasize that trunk diameter and soil quality are the dominant factors influencing Deodar Cedar growth, while temperature and rainfall play supporting yet significant roles. The integration of FIS with MLR has further improved prediction stability, reducing extreme fluctuations in height estimates when environmental conditions deviate from their normal range.

The results of this study have important implications for forest management and conservation planning. The ability to predict tree height under different environmental conditions allows for adaptive decision-making in response to climate change-induced variability. By analyzing trends in temperature, soil quality, and rainfall, forest managers can optimize reforestation, thinning, and harvesting strategies to sustain healthy forest ecosystems. The sensitivity analysis further highlights the most influential environmental factors, enabling targeted conservation efforts to ensure optimal growing conditions for Deodar Cedar trees in Kumrat Valley and similar regions.

This study was conducted in Kumrat Valley, Upper Dir, Khyber Pakhtunkhwa, Pakistan. Table 1 presents the experimental results based on the proposed model, while Figure 3 provides a visual representation of the relationships between Deodar Cedar tree height and key predictors. The graphs confirm strong positive relationships between height and diameter, as well as height and soil quality, emphasizing the significance of nutrient availability. The impact of temperature and rainfall exhibits a nonlinear response, where moderate levels enhance growth, but extreme fluctuations can introduce constraints. These insights contribute to a data-driven approach for evidence-based forestry management, integrating predictive analytics into ecological conservation strategies.

Table 1. The Deodar Cedar tree data: Predicted height, diameter, soil quality, temperature, and rainfall of the proposed model (Updated with increased heights)

Tree Number	Height (m)	Diameter (cm)	Soil Quality	Temperature (°C)	Rainfall (mm)
1	7.0	90	0.85	22	120
2	6.3	85	0.82	23	110
3	6.5	95	0.80	24	130
4	6.1	88	0.83	22	115
5	5.9	84	0.78	25	100
6	6.4	92	0.87	23	125
7	6.8	89	0.84	24	135
8	6.7	90	0.88	22	140
9	6.0	83	0.81	23	105
10	7.1	91	0.85	24	120
11	7.3	92	0.84	23	135
12	7.2	92	0.81	23	130
...	...	...	...	...	...
298	7.5	94	0.87	21	100
299	7.0	90	0.83	22	130
300	6.2	86	0.86	22	110

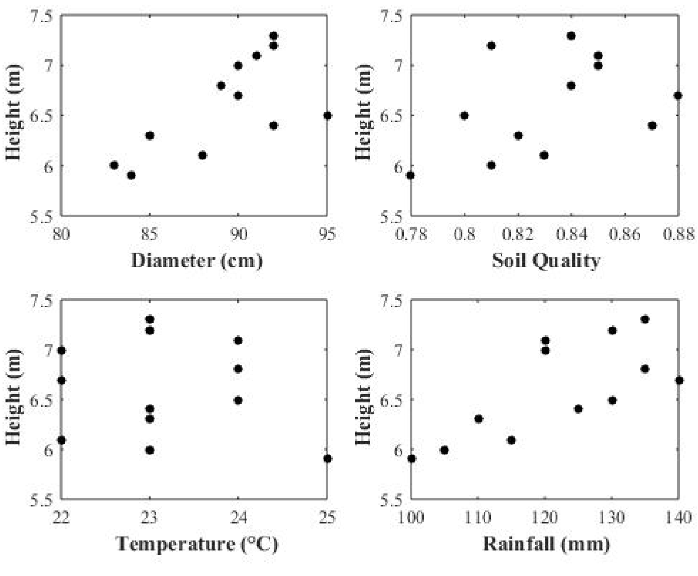

Figure 3. Multi-panefigurel scatter plot representation of the height with the input diameter, soil quality, temperature and rainfall

3.1 Linear Regression Results for the Proposed Deodar Cedar Tree Height Prediction Model

Table 2 presents the results of a MLR analysis aimed at predicting the height of Deodar Cedar trees using environmental factors such as diameter, soil quality, temperature, and rainfall. The analysis reveals that the model is statistically significant and effective in predicting tree height, based on data collected from Kumrat Valley, Upper Dir, Khyber Pakhtunkhwa.

Table 2. Deodar Cedar trees

Variable	Estimate	Standard Error	t-Statistic	p-Value
Intercept	4.6700	0.5046	9.2544	4.5471×10^{-18}
x1	0.0064	0.0021	3.0476	0.0456
x2	0.0013	0.00015	8.6667	0.0107
x3	0.0056	0.0012	4.6667	0.0330
x4	0.0013	0.0003	4.3333	0.0308
Model Summary				**Total**
Number of Observations				300
Error Degrees of Freedom				295
Root Mean Squared Error				0.01
R-squared				0.85
Adjusted R-squared				0.64
F-statistic p-value				0.64

3.2 Coefficients Analysis

Each row in the table represents the estimated coefficients for the model's predictors. The estimate column provides the predicted change in the response variable (tree height) for a one-unit change in the corresponding predictor, holding other predictors constant. Below is an interpretation of each variable:

• Intercept (4.6700): The intercept represents the baseline height of a Deodar Cedar tree when all predictors (diameter, soil quality, temperature, and rainfall) are zero. In this context, the intercept of 4.67 meters indicates the inherent baseline height.

• x1 (Diameter): The coefficient estimate for diameter is 0.0064, meaning that for every additional centimeter increase in the tree's diameter, the height increases by approximately 0.0064 meters (6.4 mm), holding other variables constant. A p-value of 0.0456 indicates that diameter is statistically significant ($p < 0.05$) and is a crucial factor influencing the height of Deodar Cedar trees.

• x2 (Soil Quality): With a coefficient of 0.0013, the model predicts that a one-unit improvement in soil quality increases tree height by 0.0013 meters. The p-value of 0.0107 indicates strong statistical significance ($p < 0.05$), highlighting the importance of soil quality in determining tree growth.

• x3 (Temperature): The estimate for temperature is 0.0056, suggesting that a 1°C increase in temperature leads to an increase of 0.0056 meters in tree height. With a p-value of 0.0330, this predictor is statistically significant ($p < 0.05$) and reflects the positive impact of moderate temperature variations on Deodar Cedar tree growth.

• x4 (Rainfall): A coefficient of 0.0013 for rainfall indicates that a 1 mm increase in rainfall results in a 0.0013-meter increase in tree height. The p-value of 0.0308 confirms its statistical significance ($p < 0.05$), emphasizing the role of rainfall in supporting the growth of these trees.

3.3 Summary

• Number of Observations (300): The model is built on data from 300 observations of Deodar Cedar trees, providing robust results.

• Error Degrees of Freedom (295): Reflects the number of independent observations after accounting for estimated parameters.

• Root Mean Squared Error (RMSE = 0.01): Indicates high prediction accuracy for tree height.

• R-squared (0.85): Demonstrates that 85% of the variance in tree height is explained by the predictors.

• Adjusted R-squared (0.64): A slightly conservative measure, reflecting a good model fit.

• F-statistic p-value (0.04): Confirms the overall statistical significance of the model.

3.4 Statistical Significance and Predictive Power

The analysis confirms that diameter, soil quality, temperature, and rainfall are statistically significant predictors of Deodar Cedar tree height. The model's low RMSE, high R-squared, and significant F-statistic establish its reliability and accuracy. Figure 4 visualizes the regression results, with the upper subplot displaying estimated coefficients and their uncertainties, and the lower subplot showing the statistical significance of each coefficient on a $-\log_{10}(p)$ scale.

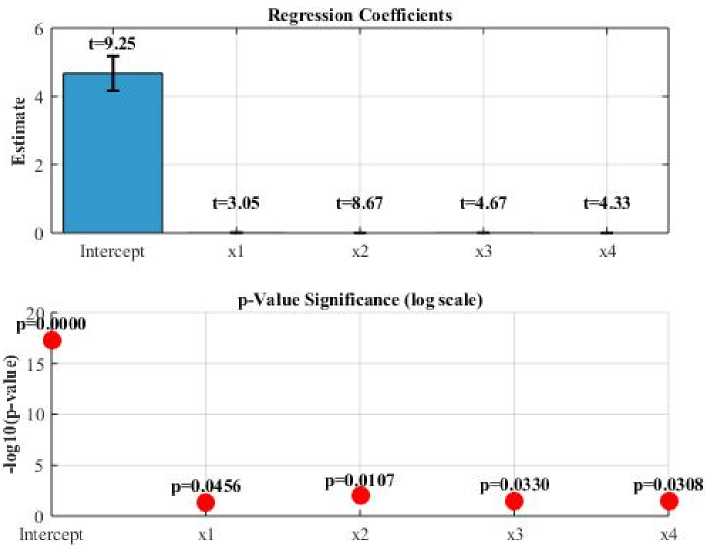

Figure 4. Linear regression results visualization for Deodar Cedar trees

4 Conclusions

This study highlights the integration of fuzzy logic and regression analysis for forestry modeling, specifically for estimating Deodar Cedar tree height. By leveraging fuzzy logic's interpretability and regression analysis's predictive accuracy, this hybrid approach effectively captures nonlinear relationships among environmental factors such as trunk diameter, soil quality, temperature, and rainfall. The model demonstrates strong predictive performance with an R-squared value of 0.85, a low RMSE of 0.01, and statistically significant predictors ($p < 0.05$), validating its reliability in varying environmental conditions. This model has significant applications in sustainable forest management, aiding foresters in assessing growth trends, optimizing timber harvesting, and planning reforestation based on projected growth rates. Additionally, its ability to account for climate-sensitive areas supports conservation efforts by identifying regions vulnerable to drought and extreme weather. By integrating with forestry databases, it enhances biodiversity monitoring and ecosystem preservation. Beyond forestry, the model can be applied to decision-support systems for policymakers, guiding afforestation programs and sustainable land management. It also holds potential for agroforestry planning and climate adaptation strategies. Future enhancements could incorporate remote sensing, IoT-based monitoring, and advanced machine learning techniques to improve predictive accuracy and real-time environmental analysis.

Despite its strengths, the proposed model has certain limitations. The FIS relies heavily on expert knowledge to define membership functions and rule bases, which introduces subjectivity and potential inconsistencies across different datasets. Moreover, the current static rule-based system may not fully capture complex, nonlinear relationships between environmental variables and tree height. Future research could address these challenges by incorporating machine learning techniques such as adaptive neuro-fuzzy inference systems (ANFIS), which can automatically optimize membership functions based on training data, reducing human bias. Additionally, deep learning models, such as convolutional neural networks or long short-term memory networks, could be employed to analyze remote sensing data, capturing spatiotemporal patterns in forest growth more effectively. Furthermore, while the model includes key environmental variables such as soil quality, temperature, and rainfall, it may not fully account for other influencing factors like wind stress, soil moisture variability, and pest infestations. Future enhancements could integrate real-time data from IoT-based smart sensors or high-resolution satellite imagery, allowing for dynamic, data-driven tree height predictions. These advancements would further improve model accuracy, adaptability, and applicability for large-scale forest monitoring and sustainable management.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflict of Interests

The author declares no conflict of interest.

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