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Statistical Analysis of Growth of coconut trees based on number of fronds affected by soil characteristics and Climate

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Abstract: ***The number of leaves in a tree is one of the visual key traits describing the development and growth of the plant. A main challenge is to analyze and model the circuitry that links the different levels of whole-plant organization in response to environmental factors: phenology, leaf, soil characteristics, climate and so on. One such challenge is studied in this paper through statistical model. A primary data is collected from two coastal districts of Tamil Nadu. The information related to number of fronds and leaves are recorded. Statistical analyses based on the number of fronds and length of leaves in coconut trees in Cuddalore and Chengalpattu districts are performed. As Cuddalore and Chengalpattu are coastal districts the influence of other factors such as soil characteristic and temperature are also discussed. This Bio -Statistical analysis aims to shed light on the intricate relationship between environmental factors and the number of fronds in the growth of coconut trees. By combining field data with robust statistical methodologies, we hope to contribute valuable insights that can guide sustainable agricultural practices and support the long-term well-being of coconut ecosystems worldwide.***

Keywords: ***Estimation of number leaves based on fronds, Impact of soil characteristics on growth coconut trees based fronds, Statistical analysis of growth coconut trees based fronds***

1. INTRODUCTION

Statistical analysis aims to shed light on the intricate relationship between environmental factors and the number of fronds in the growth of coconut trees. By combining field data with robust statistical methodologies, we hope to contribute valuable insights that can guide sustainable agricultural practices and support the long-term well-being of coconut ecosystems worldwide. The interest in this field has begun since, 1995 by TSG Peiris, RO Thattil and R Mahindapala [4]. In 2015 an analysis of the effect of climatic factors on the growth of the coconut trees were studied by Großkinsky et al., [10]. The development of recent Convolutional Neural Network (CNN)-based techniques was conducted by researchers (To cite a few [18], [11], [16], [24]) wherein visual leaf counting has attracted considerable attention. In 2017 the number of leaves a plant has been one of the visual key traits (phenotype) describing its development and growth was studied by Dobrescu et al., [8]. Several researchers have considered various analysis based on various factors affecting the growth of plants (To cite a few [9],[15],[21],[12],[13],[17],[14], [19], [6], [20]) Therefore, the growth of coconut trees is a captivating process that not only sustains the environment but also supports the livelihoods of communities in tropical regions. The multifaceted uses of coconut trees underscore their importance in agriculture, industry, and culture.

This paper aims to conduct a comprehensive statistical analysis to explore the relationship between various factors and the number of fronds in the growth of coconut trees. Factors such as soil composition, climate conditions, water availability, and agricultural practices are known to influence the development of coconut trees. By employing statistical methods, we seek to identify significant correlations and potential predictors that contribute to the optimal frond count in these trees.

This paper is organized as follows: Section 1 give introduction and literature review. Section 2 gives the background of the study. Section 3 gives the statistical analysis of the data obtained. Section 4 records the inferences and suggestions. Section 5 concludes the paper.

2. BACKGROUND OF THE DATA

Objective of study:

Analyze the various factors affecting the growth of coconut tree through statistical model. Primary data was procured to study the same.

Cuddalore district

The primary data has been collected from the coastal district of Cuddalore, the village named Valayamadevi from the block of Melbhuvanagiri from the agricultural lands of sandy clay loam soil. The sample population is 24 coconut trees. The length of the coconut tree leaves and the number of the fronds in coconut trees has been counted manually from the sample population during the Christmas vacation with help of farmers for 10 days from 23.12.2023 to 02.01.2024. The agro climatic zone of this particular land follows from the Cauvery Delta Zone Submit your manuscript electronically for review.

Chengalpattu District

The following data has been collected from the coastal district of Chengalpattu, the village named Thondamanllur from the block of Lathur from the agricultural lands of sandy clay loam soil. The sample size is 24 coconut trees. The length of the coconut tree leaves and the number of the fronds in coconut trees has been counted manually from the sample population during the Pongal holidays from 14.01.2024 to 17.01.2024. The agro climatic zone of this particular land follows from the North Eastern Zone.

3. STATISTICAL ANALYSIS

Statistical analysis based on correlation and regression is performed between the length of leaves and number of fronds in each districts using R language.

Cuddalore District : The diagrammatic representation of the correlation is shown in Fig 1

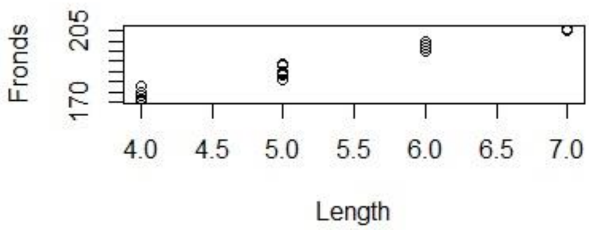
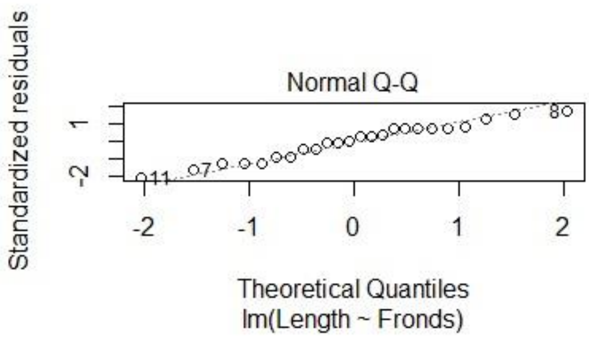


Fig 1:

Using machine learning process a regression equation for the same is modeled as shown in Fig 2.



Correlation: 0.978

(Intercept)   Fronds

-10.29082507   0.08268861

Fig 2:

The strength of relation is tested by ANOVA as shown in the following

Df Sum Sq Mean Sq F value Pr(>F)

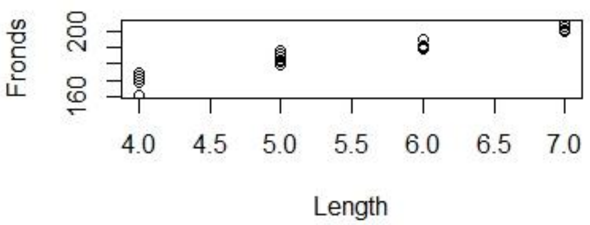
Fronds 1> summary(two.way)

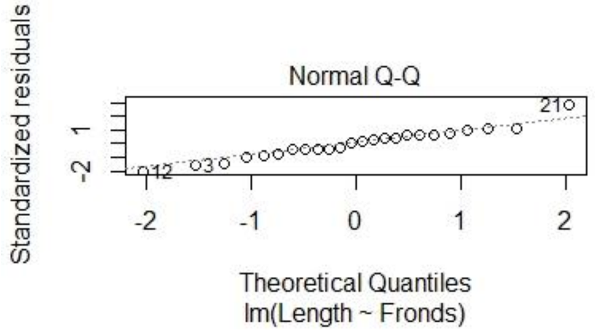
Df Sum Sq Mean Sq F value Pr(>F)

Fronds 1 21.947 21.947 477.4 <2e-16 ***

Residuals 22 1.011 0.046

Chengalpattu District: The analysis related to data obtained from this district are shown in the following:





(Intercept) Fronds

-11.05120482 0.08866717

Correlation: 0.963

ANOVA ALANYSIS:

```
Fronds       1 27.841  27.841   283.8 4.66e-14 ***
Residuals   22  2.159   0.098
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Fig 3:

4. INFERENCES

Through the above statistical analysis performed in both the districts, we were able to model a relationship between the length of the coconut leaves and number of fronds. Also we infer that there exist a strong correlation between them in both the places. The regression model could be utilized for prediction of the values of the variable.

The larger value of F in both the cases infer that the variations are not by chance. The low p value indicate that both the variables have more effect on each other. Thus the strong relationship between the variables are tested significantly.

Influences of soil characteristic and climate:

The slight difference in temperature and soil characteristic has an effect on growth of the plant based on the number of fronds. The same was tested and the results are in the following:

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
FrondsB	1	175	175.4	1.146	0.296
Residuals	22	3366	153.0		

From the low value of F we infer that there is a significant difference in both the places on growth of plant based on number of fronds. The qualitative nature of soil characteristic and climate factors has an effect on the growth of the plant along with phenotype features. This calls for better model to study the growth of plants and predict the variable in more effective way.

5. CONCLUSION

Preliminary analysis suggests that there is no significant relationship in the number of fronds and length of leaves in coconut trees in Cuddalore and Chengalpattu. Additionally, qualitative findings shed light on the other different factors which may include similarity on soil texture (sandy clay loam soil), different agro-climatic zones (i.e. Cuddalore belongs to Cauvery delta zone and Chengalpattu belongs to North eastern zone), etc. These results underscore the importance of agricultural practices in different places yet tend to give the optimal yield and minimizing resource inputs taking into consideration the other physical factors also.

This study has been done considering the length and number of coconut tree fronds, the soil texture and temperature of the lands and the project is still open to all to include the other factors such as thickness of the coconut fronds, cultivation practices, rainfall and many more. This project has been done with respect to Cuddalore and Chengalpattu but it can also be extended by taking data from all the other districts of the state which can give the better details about the geographical land structure which can give the best yield. In search of quantifying data, a concept which has been rapidly growing for more than half a decade namely Fuzzy set theory ([22], [23], [7], [1], [2], [3]), Big Data and Bayesian statistics developed by several researchers can also be implemented

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