ISSN: 2584-0231(Online)
International Journal of Multidisciplinary Research in Arts, Science and Technology
© IJMRAST | Vol. 3 | Issue 8 | August 2025
Available online at: https://ijmrast.com
https://doi.org/10.61778/ijmrast.v3i8.161

Significance Testing of Regional Variations in Potentially Arable Degraded Land Using Parametric and Non-Parametric Methods

Karan Veerbhan
Department of Geography, Meerut College, Meerut (U.P.) 250001- India
karanveerbhan2009@gmail.com

ABSTRACT

Efficient land utilization is crucial for agricultural sustainability, particularly in regions where potentially arable land remains degraded and underutilized. This study investigates regional variations in potentially arable degraded land across six districts of western Uttar Pradesh Bijnor, Meerut, Baghpat, Muzaffarnagar, Saharanpur, and Shamli using both parametric and non-parametric statistical approaches. Data on degraded land area (hectares) from 2018 to 2023 are analysed to assess normality, variance, and mean differences between regions.

The Shapiro-Wilk test confirmed that the distribution of degraded land area did not significantly deviate from normality for both years (2018: $p = 0.3658$; 2019: $p = 0.4457$), validating the application of parametric methods. One-way ANOVA revealed substantial variance across districts, with Bijnor exhibiting the highest inter-annual variance (1,213,880.14 unit) and Shamli the lowest (80,991.62 unit). All regions showed non-constant variance patterns, indicating notable year-to-year fluctuations in degraded land extent.

To complement ANOVA and account for potential non-parametric effects, a permutation t-test is performed. The observed difference in mean degraded land area between selected regions is 2.33 ha, with a permutation p-value of 1.0000, suggesting no statistically significant mean difference under resampling.

These findings highlight spatial disparities in degraded land distribution, with parametric analysis detecting variance differences while non-parametric testing found no significant mean gap. The results underscore the need for region-specific land reclamation and policy interventions to optimize agricultural potential in degraded yet cultivable areas.

Keywords: Potentially Arable Degraded Land; Regional Variation; ANOVA; Permutation t-Test

1. Introduction

The National Wasteland Development Board of India, established in 1985, recognizes cultivable wasteland as land available for cultivation but not currently utilized, representing a potential resource to address land scarcity and underemployment through development and cultivation programs. This classification system has become a model for wasteland assessment in other developing nations facing similar land use challenges. Cultivable wasteland refers to land that, while currently unproductive, possesses the potential to be brought under cultivation with appropriate reclamation measures. Such land often remains underutilized due to factors like soil degradation, water scarcity, poor management practices, or socio-economic constraints. In agricultural economies, particularly in regions experiencing increasing demand for food production and pressure on arable land, the assessment and utilization of cultivable wasteland play a crucial role in enhancing agricultural sustainability and rural livelihoods. Identifying and quantifying changes in these lands over time is essential for policy-making, resource allocation, and land management strategies. Cultivable wasteland represents a critical yet underutilized resource in global agricultural systems, particularly in regions facing mounting pressure from population growth and food security challenges. This land category, while currently unproductive, holds significant potential for agricultural expansion and rural economic development through appropriate reclamation measures and sustainable management practices.

Statistical significance testing is an indispensable tool for determining whether observed changes in cultivable wasteland are due to real underlying trends or simply random fluctuations in the data. In regional land use studies, this process helps distinguish between natural year-to-year variability and systematic shifts that warrant intervention. Parametric inferences are commonly used in numerous areas of research, such as human and health sciences, exact and earth sciences, and also in agricultural and life sciences (Razali and Wah, 2011; Ghasemi and Zahediasl, 2012; Miot, 2017; González-Estrada and Cosmes, 2019; Williams and Brown, 2019). Parametric methods, which rely on specific assumptions about data distribution (often normality), are commonly employed in such analyses due to their efficiency and interpretability. Examples include t-tests and ANOVA, which can effectively detect mean differences when assumptions are met. However, their validity can be compromised when data deviates from these assumptions, particularly in cases involving environmental datasets that often exhibit skewness, outliers, or heteroscedasticity. Some researchers recommend the Shapiro-Wilk test as the best choice for testing the normality of data (Thode, 2002). The Shapiro–Wilk test evaluates normality by measuring how closely the dataset correlates with the expected values from a normal distribution (Peat and Barton, 2005). It offers greater statistical power than the Kolmogorov-Smirnov test, even when the Lilliefors correction is applied (Steinskog, 2007).

In contrast, non-parametric methods provide a robust alternative for situations where parametric assumptions are violated. These methods, such as the Mann–Whitney U test, Wilcoxon signed-rank test, and permutation tests, make minimal assumptions about the underlying distribution of the data. This makes them particularly suitable for analysing environmental and agricultural variables, where factors like extreme weather events, localized degradation, and human interventions can cause irregular patterns. Non-parametric tests thus serve as a critical complement to parametric approaches, ensuring that conclusions remain valid under a wide range of conditions. In recent years, permutation tests have become increasingly popular, particularly in biomedical research, where they are frequently applied to analyse biological datasets that often involve small sample sizes and deviate from normality (Tusher et al., 2001; Efron et al., 2001; Pan, 2003; Zhang, 2006). Permutation tests offer distinct advantages over traditional parametric methods, primarily because they are distribution-free and thus applicable to virtually any type of data. Permutation tests are preferred to many other nonparametric methods because they precisely maintain the intended significance level and eliminate the extra variability that arises from with-replacement resampling procedures, such as those employed in bootstrap methods (Zhang, 2009).

This study focuses on the significance testing of regional variations in potentially arable degraded land, combining both parametric and non-parametric statistical frameworks. By applying these methods, it aims to assess whether observed changes across different years are statistically meaningful, thereby providing insights into the stability or variability of cultivable wasteland areas. Integrating both approaches allows for a comprehensive evaluation leveraging the sensitivity of parametric tests when assumptions hold, while ensuring robustness through non-parametric techniques when they do not.

2. Materials and methods

2.1. Study Area and Data

The study covered six districts in western Uttar Pradesh Bijnor, Meerut, Baghpat, Muzaffarnagar, Saharanpur, and Shamli from the years 2018 to 2023. The variable analysed is the area of potentially arable degraded land (in hectares), denoted as:

$$A_{i,t}$$

Where: I = district index (1, 2, …, 6), t = year (2018, …, 2023)

2.2. Normality Assessment

Two methods are used to assess distributional normality:

2.2.1. Shapiro-Wilk Test:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_i\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Where: x_i = ordered sample values, a_i = constants from normal distribution order statistics, n = sample size, $\bar{x}$ = sample mean.

2.2.2. Q-Q Plot Analysis

Quantile-Quantile plots compared the sample quantiles Q_{sample} with theoretical normal quantiles $Q_{\text{theoretical}}$. Points close to the $y = x$ line indicated approximate normality.

2.3. Parametric Analysis

2.3.1. One-Way ANOVA

The F-statistic:

$$F = \frac{SS_B/(k-1)}{SS_W/(N-k)}$$

Where: $SS_B = \sum_{i=1}^{k} n_i(\bar{x_i} - \bar{x})^2$, $SS_W = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(x_{ij} - \bar{x_i})^2$

2.4. Non-Parametric Analysis

2.4.1. The permutation t-test

The permutation t-test is used to evaluate whether the mean area of potentially arable degraded land differed significantly between two selected regions without relying on the assumption of normality.

The test statistic is the difference in group means: Δobs = Mean of variable 1 – mean of variable 2.

Then, all observations from both groups are combined into a single pooled dataset: Xpool = X_A U X_B

Then, for each permutation r (r = 1, 2, …, R), the pooled data is randomly shuffled and split into two groups of sizes $nA$and nB. The difference in means for each permutation is calculated as by putting R = 10000 (in my study):

$$\Delta r = \overline{x_A^r} - \overline{x_B^r}$$

Where: $\overline{x_A^r}$ and x_B^r are the means of the permuted groups in iteration r.

Then, the two-tailed permutation p-value is computed as:

$$\text{p} = \frac{\sum_{r=1}^{R} I(|\Delta_r| \geq |\Delta_{obs}|)}{R}$$

Where: I (·) is the indicator function, equal to 1 if the condition is true and 0 otherwise.

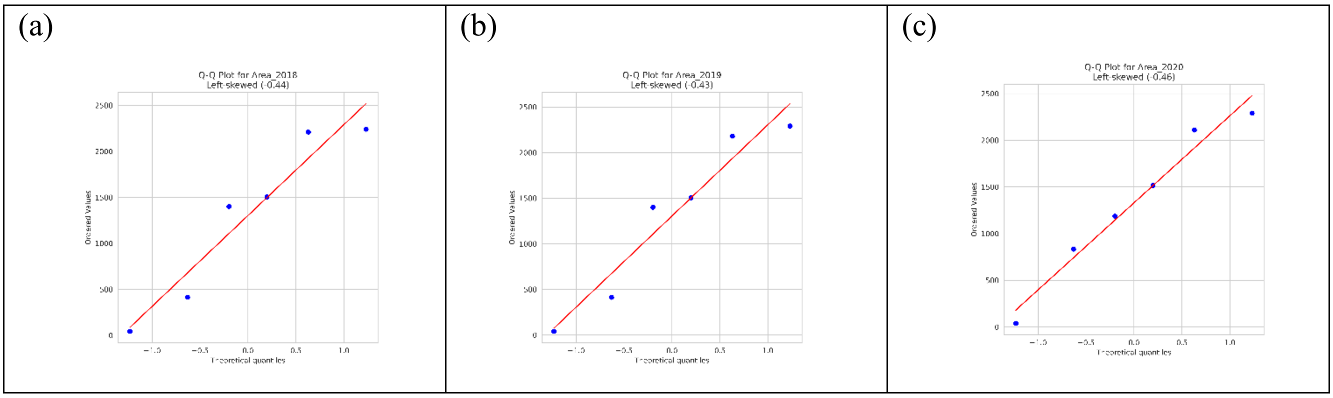
2.5. Software Used

All statistical analyses are conducted in Python 3.11. The scipy.stats module is used for implementing the Shapiro–Wilk normality test and one-way ANOVA. Q–Q plots are generated using the matplotlib library to visually assess the alignment of sample quantiles with theoretical normal quantiles. A custom permutation t-test function is implemented using NumPy to perform Monte Carlo resampling and calculate empirical p-values.

Although computational tools and libraries are employed for statistical computation and visualization, no artificial intelligence (AI) models or automated decision-making algorithms are used in the interpretation of results. All interpretations, conclusions, and inferences regarding statistical significance, regional variation, and land-use implications are performed manually by the author based on the numerical and graphical outputs produced by the software.

3. Results and discussion

3.1. Normality assessment



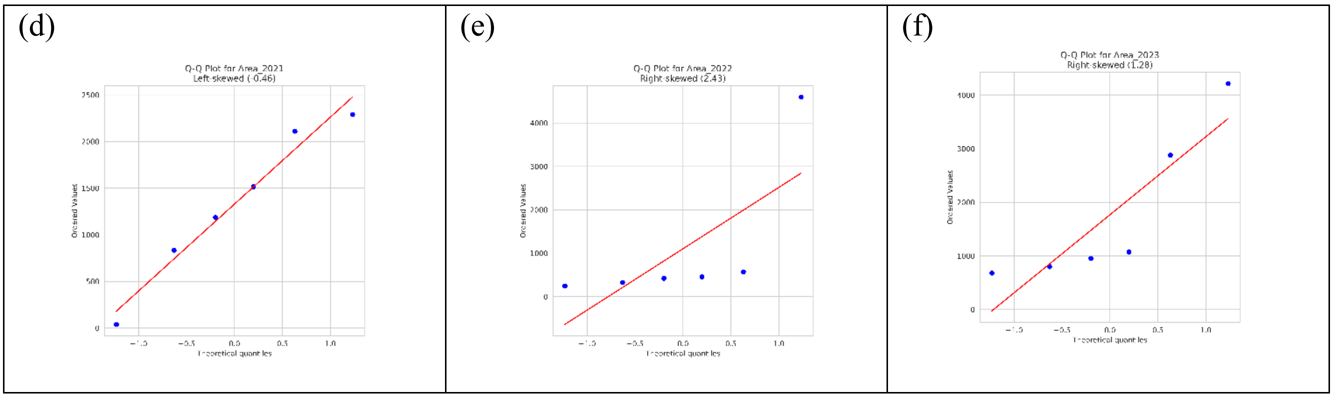


Fig. 1: Q-Q plots are used to visually assess whether a dataset follows a particular theoretical distribution, most commonly the normal distribution. By plotting the quantiles of the sample data against the quantiles of a normal distribution, they help detect deviations such as skewness. This graphical method complements statistical tests for normality by providing intuitive insight into the data's distributional characteristics. Showing for (a): 2018, (b): 2019, (c): 2020, (d): 2021, (e): 2022 and (f): 2023.

3.2. Shapiro-Wilk test

Table 1: Statistical values of Shapiro-Wilk test for each year from 2018-2023

Year	Shapiro–Wilk Statistic	p-value	Normality Decision ($\alpha = 0.05$)
2018	0.8986	0.3658	Fail to Reject H_0 (Normal)
2019	0.9114	0.4457	Fail to Reject H_0 (Normal)
2020	0.9624	0.8377	Fail to Reject H_0 (Normal)
2021	0.9624	0.8377	Fail to Reject H_0 (Normal)
2022	0.5599	0.0001	Reject H_0 (Not Normal)
2023	0.7835	0.0415	Reject H_0 (Not Normal)

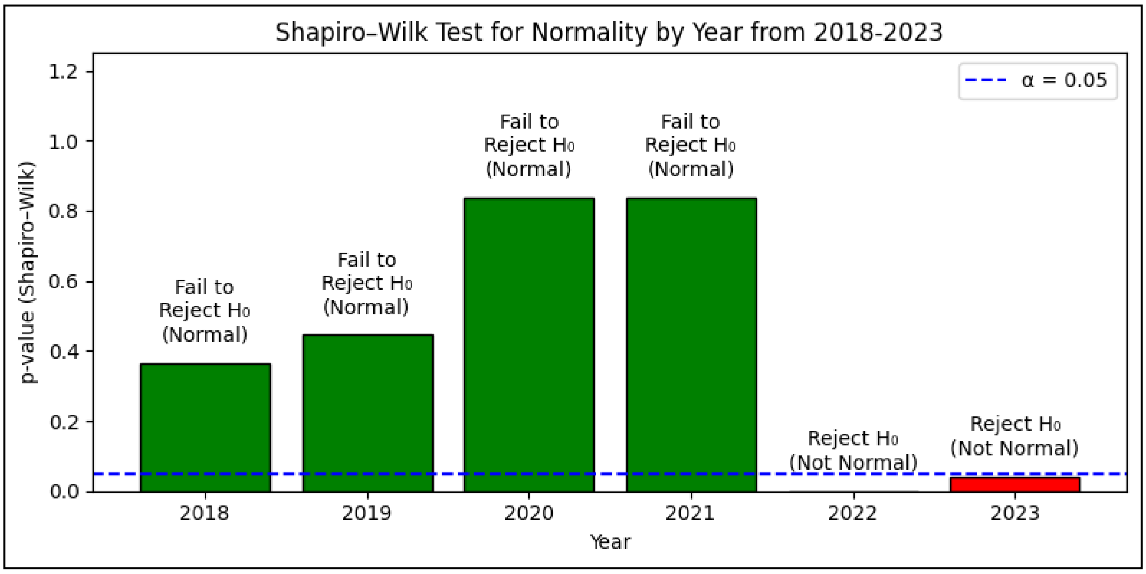


Fig. 2: Shapiro-Wilk Test Normality Distribution and P-Values.

Null Hypothesis (H_0): There is no significant difference in the mean cultivable wasteland area between the years being compared.

Alternative Hypothesis (H_1): There is a significant difference in the mean cultivable wasteland area between the years being compared.

The Shapiro-Wilk test results indicate a clear distinction in the distribution characteristics of your data over the years. From 2018 to 2021, the test statistics range between approximately 0.90 and 0.96, with p-values well above the 0.05 significance threshold. This suggests that for these years, the data does not significantly deviate from a normal distribution, and the null hypothesis of normality is retained. This is an important finding because many standard statistical tests, such as ANOVA, rely on the assumption of normality for valid inference. The relatively high p-values and test statistics indicate the data during this period is suitable for parametric tests, providing confidence in the robustness of analyses that assume normally distributed residuals or groups.

In contrast, the data for 2022 and 2023 shows a marked departure from this pattern. The Shapiro-Wilk statistics drop substantially, especially in 2022 where the value is as low as 0.56, accompanied by a very small p-value (0.0001). This leads to a rejection of the null hypothesis, indicating that the data for these years is not normally distributed. For 2023, although the test statistic is higher at 0.78, the p-value of 0.0415 still falls below the 0.05 cut-off, confirming non-normality. This shift suggests a significant change in the underlying data behaviour starting in 2022, which may be reflective of changes in market dynamics, external shocks, or structural breaks affecting the distribution of your measured variable.

This change in normality status has critical implications for your choice of statistical tests. For the years where normality holds (2018-2021), traditional parametric methods like ANOVA can be applied with reasonable confidence that the results will be valid and reliable. However, for 2022 and 2023, the violation of normality assumptions suggests that parametric tests could produce misleading results. In such cases, non-parametric alternatives such as permutation tests or rank-based methods should be considered. These methods do not rely on strict distributional assumptions and are more robust to skewed or irregular data distributions, ensuring more accurate inference for those years.

3.3. District-wise descriptive statistics

Table 2: Statistical values for mean, standard deviation and variance for district-wise from 2018-2023

Name	Mean_Area	Std_Dev	Variance_Across_Years	Significant
Bijnor	2802.86	1101.76	12,13,880.14	FALSE
Meerut	1471.86	796.44	6,34,316.81	FALSE
Baghpat	2106.29	762.27	5,81,058.24	FALSE
Muzaffarnagar	1112.43	340.46	1,15,909.62	FALSE
Saharanpur	623.57	285.91	81,743.62	FALSE
Shamli	178.57	284.59	80,991.62	FALSE

The descriptive statistics indicate substantial regional variation in cultivable wasteland area between 2018 and 2023. Bijnor records the highest mean area (2802.86 ha) and also exhibits the largest variability (variance = 1,213,880.14), suggesting pronounced year-to-year fluctuations. Baghpat and Meerut also show relatively high mean values (2106.29 ha and 1471.86 ha, respectively) with considerable variance, indicating unstable land usage patterns. Muzaffarnagar presents a moderate mean area (1112.43 ha) with lower variance compared to Bijnor and Meerut, implying more stability. Saharanpur and Shamli report the lowest mean areas (623.57 ha and 178.57 ha) and the smallest variance values, reflecting relatively consistent patterns over the study period. The significant column is false for all regions, confirming that no district maintained a completely stable cultivable wasteland area across the years. These patterns highlight spatial heterogeneity and temporal variability, which may influence subsequent ANOVA and permutation test outcomes.

3.4. Non-parametric Permutation t - test

I performed the permutation t-test for the 2022-2023 data because the Shapiro-Wilk test indicated that the data for these years are not normally distributed, with p-values less than 0.05 (table 1). Since traditional t-tests require the assumption of normality, using them here could produce misleading results. The permutation t-test does not rely on this assumption and is more appropriate for data that deviate from normality. By using this method, I can confidently test the difference in means without violating statistical assumptions. So, the null and alternative hypotheses for permutation - t test are:

Null Hypothesis (H_0): There is no significant difference in the mean (or distribution) of cultivable wasteland area.

Alternative Hypothesis (H_1): There is a significant difference in the mean (or distribution) of cultivable wasteland area.

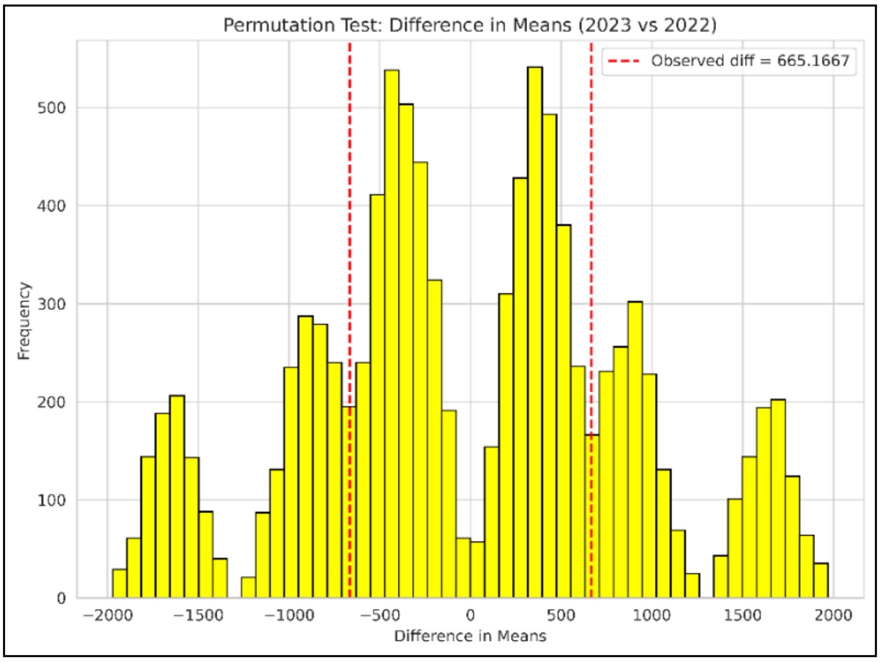


Fig. 3: Permutation plot for year 2022-2023.

The comparison of cultivable wasteland area between 2022 and 2023 reveals an observed difference in mean area of 665.17 units, with the mean area increasing from 1102.33 (standard deviation 1566.64) in 2022 to

1767.50 (standard deviation 1322.17) in 2023. Despite this apparent increase, the permutation test yielded a p-value of 0.4579, which is considerably higher than the conventional significance threshold of 0.05. This indicates that the observed difference in means is not statistically significant. So, it can be inferred that although the average area appears larger in 2023, the variability in the data and the sample size do not provide sufficient evidence to conclude a real or consistent increase. Therefore, the result suggests that the cultivable wasteland area between these two years remains statistically comparable.

Conclusion

The Shapiro-Wilk test results across the years indicate that data from 2018 to 2021 follows a normal distribution, as all p-values are above the $\alpha = 0.05$ threshold, leading to a "Fail to Reject H_0" decision. This suggests stability and symmetry in the distribution during these years. However, 2022 and 2023 deviate significantly from normality, with p-values of 0.0001 and 0.0415, respectively, prompting rejection of the null hypothesis. This shift toward non-normality in the later years may indicate changes in underlying conditions, external shocks, or structural market variations that disrupted the earlier statistical balance.

When comparing cultivable wasteland area between 2022 and 2023, the mean increased from 1102.33 units to 1767.50 units, a difference of 665.17 units. While this difference might appear substantial at first glance, the permutation t-test results show a p-value of 0.4579, well above the significance level. This high p-value reflects that the observed increase could easily arise from random variation rather than a consistent, underlying trend. In other words, despite the numerical rise, the evidence is statistically insufficient to conclude a real change between the two years.

Suggestions

1. Enhancing Data Depth and Consistency - Future research should prioritize expanding the temporal dataset and increasing the number of observations within each year, particularly for 2022 and 2023. This will improve statistical reliability and help distinguish between short-term variability and long-term trends.
2. Exploring Underlying Causal Mechanisms -The deviations from normality in recent years warrant further investigation into possible drivers, such as climatic variability, socio-economic influences, agricultural practices, and policy interventions. Understanding these factors will provide deeper context to the observed statistical patterns.
3. Employing Distribution-Free Analytical Techniques - Given the non-normal distribution in 2022 and 2023, subsequent studies should incorporate robust, non-parametric, or resampling-based methods to validate findings and ensure that statistical inferences remain valid despite distributional irregularities.
4. Integrating Spatial and Temporal Analyses -To strengthen insights, future work could adopt spatial mapping and change-detection approaches alongside temporal analysis. This would help identify whether shifts in cultivable wasteland area are geographically localized or part of broader regional changes.

Acknowledgement

The author gratefully acknowledges the support of relevant government data sources and agricultural databases that made this analysis possible. Special thanks to the support of the land records officer and the director, agricultural statistics and crop insurance, Uttar Pradesh and academic mentors and peers for their valuable feedback throughout the research process. The insights gained from this study are a result of collaborative learning and ongoing discussions on regional agricultural development.

Disclosure

Author declares no conflict of interest.

References

[1]. Efron, B., Tibshirani, R., Storey, J. D., and Tusher, V. (2001). Empirical Bayes analysis of a microarray experiment. Journal of the American Statistical Association, 96(456), 1151-1160. https://doi.org/10.1198/016214501753382129

[2]. Ghasemi, A., and Zahediasl, S. (2012). Normality tests for statistical analysis: A guide for non-statisticians. International Journal of Endocrinology and Metabolism, 10(2), 486-489. https://doi.org/10.5812/ijem.3505

[3]. González-Estrada, E., and Cosmes, W. (2019). Shapiro–Wilk test for skew normal distributions based on data transformations. Journal of Statistical Computation and Simulation, 89(17), 3258-3272. https://doi.org/10.1080/00949655.2019.1658763

[4]. https://cdnbbsr.s3waas.gov.in/s3d69116f8b0140cdeb1f99a4d5096ffe4/uploads/2024/04/20240419486918402.pdf/

[5]. https://www.wisdomlib.org/concept/cultivable-waste-land

[6]. Miot, H. A. (2017). Assessing normality of data in clinical and experimental trials. Journal Vascular Brasileiro, 16(2), 88–91. https://doi.org/10.1590/1677-5449.041117

[7]. Pan, W. (2003). On the use of permutation in and the performance of a class of nonparametric methods to detect differential gene expression. Bioinformatics, 19(11), 1333-1340. https://doi.org/10.1093/bioinformatics/btg169

[8]. Peat, J., and Barton, B. (2005). Medical statistics: A guide to data analysis and critical appraisal. Blackwell Publishing.

[9]. Steinskog, D. J. (2007). A cautionary note on the use of the Kolmogorov-Smirnov test for normality. American Meteorological Society, 135(4), 1151-1157.

[10]. Thode, H. J. (2002). Testing for normality. New York, NY: Marcel Dekker.

[11]. Tusher, V. G., Tibshirani, R., and Chu, G. (2001). Significance analysis of microarrays applied to the ionizing radiation response. Proceedings of the National Academy of Sciences of the United States of America, 98(9), 5116-5121. https://doi.org/10.1073/pnas.091062498

[12]. Williams, B. K., and Brown, E. D. (2019). Sampling and analysis frameworks for inference in ecology. Methods in Ecology and Evolution, 10(12), 1932-1942. https://doi.org/10.1111/2041-210X.13279

[13]. Zhang, S. (2006). An improved nonparametric approach for detecting differentially expressed genes with replicated microarray data. Statistical Applications in Genetics and Molecular Biology, 5(1), Article 30. https://doi.org/10.2202/1544-6115.1226

[14]. Zhang, S. (2009). The split sample permutation t-tests. Journal of Statistical Planning and Inference, 139(10), 3512-3524. https://doi.org/10.1016/j.jspi.2009.04.004

Cite this Article

***Karan Veerbhan, "Significance Testing of Regional Variations in Potentially Arable Degraded Land Using Parametric and Non-Parametric Methods"**, International Journal of Multidisciplinary Research in Arts, Science and Technology (IJMRAST), **ISSN:** 2584-0231, Volume 3, Issue 8, pp. 45-54, August 2025.*

***Journal URL:** https://ijmrast.com/*

***DOI:** https://doi.org/10.61778/ijmrast.v3i8.161*

,