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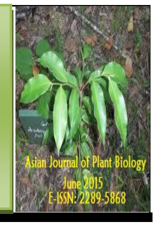

Short Communication

Test for the Presence of Autocorrelation in Modified Gompertz Model used for Modelling the Growth of Callus Cultures from *Glycine wightii* (Wight & Arn.) Verdc.

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ABSTRACT

Glycine wightii species is an important perennial soybean. Tissue culture of *in vitro* cells, tissues and organs of *Glycine wightii* can yield efficient means in the genetics of breeding genetics, understanding the physiology and biochemistry of legumes. Most often than not, callus growth curve is sigmoidal in characteristics. In this work, we model callus growth from *Glycine wightii* from published literature to acquire essential growth constants. Previously, we model the growth of callus of *Glycine wightii* from published literature to obtain vital growth constants. We discovered that the modified Gompertz model via nonlinear regression utilizing the least square method was the best model to explain the growth curve. Nonlinear regression utilizing the least square method typically utilizes the idea that data points usually do not depend upon each other or the value of a data point is not determined by the value of previous or proceeding data points or usually do not display autocorrelation. In this work, the Durbin-Watson statistic to check for the presence of autocorrelation in the growth model was carried out, and showed that the modified Gompertz model was adequate to model the callus growth curve.

INTRODUCTION

Glycine wightii is an important climbing vine-like perennial soybean species native to Brazil and Africa [1]. Tissue culture of in vitro cells, tissues and organs of *Glycine wightii* can yield efficient means in the genetics of breeding genetics, comprehending the physiology and biochemistry of legumes. Additionally it may be applied to the creation of plant biomass, plant enhancement, as a mean for studying protein synthesis, and production of secondary metabolites [2,3]. *Glycine wightii in vitro* culture has been reported from leaves [4] and cotyledons and hypocotyls [5]. Callus production is definitely an essential instrument to study plant regulation, biosynthesis and biochemistry [6]. Probably the most crucial initial examination of callus characteristics is the growth qualities [7]. Most of the time, callus growth curve is sigmoidal in qualities. Regularly, plant scientists researching callus growth ignore the usage of mathematical growth that are beneficial in acquiring important growth constants for example lag period, maximum specific growth rate and maximum growth or asymptote. Every single of these constants is helpful for additional modelling.

We have utilized several growth models (manuscript in preparation) to model the growth of *Glycine wightii* callus from a published literature [7]. We learned that the modified Gompertz model via nonlinear regression using the least square method was the most effective model to explain the callus growth curve (manuscript in preparation). Nonlinear regression using the least square method generally makes use of the assumption that data points tend not to rely on each other or the value of a data point is not determined by the value of prior or proceeding data points. Autocorrelation in between data could happen as a result of situations for instance temperature drift in the course of time measurements or perhaps an over-used tungsten lamp in a spectrophotometer. For instance, growth of microorganisms where the increase in cellular number in a given time frame can be exponentially fast and any event in time that effect the current or past number of cells would be seen in an amplified manner in future times or exhibited autocorrelation. If a person would count the number of animals every year in a provided area, the data is going to be particularly autocorrelated and nonindependence as the number of animals inside an current year is going to be extremely affected by the number of animals within the last year [8].

In this work, the Durbin–Watson statistic for the presence of autocorrelation in the growth of *Glycine wightii* as modelled using the modified Gompertz model would be used. The method calculates the level of significance in accordance to the method proposed by Draper and Smith [9].

METHODS

Acquisition of Data

In order to process the data, the graphs were scanned and electronically processed using WebPlotDigitizer 2.5 [10] which helps to digitize scanned plots into table of data with good enough precision [11]. Data were acquired from the works of Silva et al. [7] from Figure 1 and then replotted (**Fig. 1,** with permission) (Shukor, M.S., Masdor, N.A., Shamaan, N.A., Wan Johari, W.L. and Shukor, M.Y 2015. Modelling the growth of callus cultures from *Glycine wightii* (Wight & Arn.) Verdc. Manuscript in preparation).

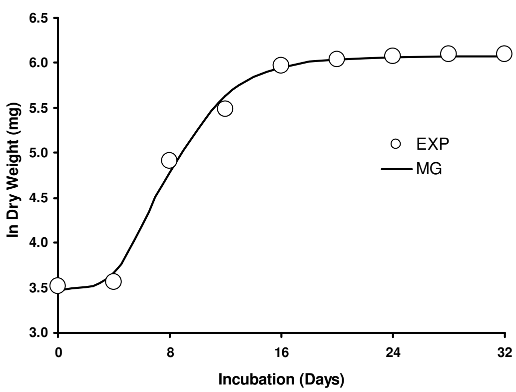

Fig. 1. Growth curves of *Glycine wightii* callus modelled using the modified Gompertz (MG) model.

Durbin-Watson test

Draper and Smith [9] outlined a method to calculate the Durbin–Watson statistic as follows;

$$d=\frac{\sum_{t=2}^{T}\left(\hat{e}_t-\hat{e}_{t-1}\right)^2}{\sum_{t=1}^{T}\hat{e}_t^2} \qquad (1)$$

The hypothesis H_0: $\rho= 0$ versus the alternative $H1$: $\rho > 0$ is tested. The statistic is about equal to $2(1- p)$. The Durbin-Watson test statistic equals 2 when the ρ value is zero while a ρ value of one equals a Durbin-Watson test statistic of 0. Non-autocorrelation is specified by a d value near 2 while a value towards 0 indicates positive autocorrelation. Negative autocorrelation is indicated by d values nearing 4 (**Eqn**. 1).

The decision rule for the Durbin-Watson bounds test is

- if d > upper bound, fail to reject the null hypothesis of no serial correlation,
- if d < lower bound, reject the null hypothesis and conclude that positive autocorrelation is
present,
- if lower bound < d < upper bound, the test is inconclusive.

The null hypothesis should be rejected for a low value of the Durbin-Watson test statistic indicating significant autocorrelation. Unlike the t- or z-statistics, the distribution of the Durbin-Watson test statistic is not available for ρ-value associated with d and tables must be used in the hypothesis testing.

RESULTS AND DISCUSSION

The phenomenon of autocorrelation is observed when covariances of errors are not zero, a problem often seen in time series data such as microbial growth curves. A consequent of the presence of autocorrelation is that estimators for the models used even though are still considered linear and unbiased, but they there not efficient and not the best. The runs test has additionally been utilized as a method to test for autocorrelation in time-series regression models. Nonetheless, simulation studies employing Monte Carlo have demonstrated that the runs test generates noticeably asymmetrical error rates in the two tails [12]. The investigation is carried out to analyse the empirical properties of the runs test utilizing (a) sample sizes of between 12 and 100 (b) using non-intervention and intervention regression models, (c) utilizing directional and nondirectional tests (d) with three levels of α, and (e) with 19 levels of autocorrelation among the errors. In addition, both directional and nondirectional tests produce no satisfactory results with respect to Type I error. The increase of the ratio of degrees of freedom to sample size to as high as 0.98 could also not remedy the situation. Hence, the Durbin-Watson method would be the method of choice to assess autocorrelation.

The Durbin–Watson statistic (DW) can calculate for the presence of serial correlation of residuals. Autocorrelation, also known as serial correlation, is the cross-correlation of a signal with itself. The DW is used to test whether a model has been successful in describing the underlying trend. Informally, it is the similarity between observations as a function of the time lag between them. It is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal obscured by noise [8,9,13].

As usual the hypothesis H_0: $\rho= 0$ versus the alternative $H1$: $\rho > 0$ is tested. The statistic is approximately equal to $2(1- p)$. The value of the Durbin-Watson statistics was d = 0.189/0.054=3.49. The Durbin-Watson test statistic equals 2 when the ρ value is zero while a ρ value of one equals a Durbin-Watson test statistic of 0. a d value near 2 indicate non-autocorrelation while a value towards 0 indicates positive autocorrelation. Generally, d values nearing 4 indicates negative autocorrelation. The null hypothesis should be rejected for a low value of the Durbin-Watson test statistic indicating significant autocorrelation.

Unlike the t- or z-statistics, the distribution of the Durbin-Watson test statistic is not available for ρ-value associated with d

and tables must be used in the hypothesis testing. For a three-parameter model like the modified Gompertz model, the upper critical value d_U was 1.875 while the lower critical value d_L was 0.279. Since the d value was higher than the upper critical, then the null hypothesis that there is no positive autocorrelation is not rejected and the modified Gompertz model used for fitting the growth curve was adequate.

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