



A GAMLSS approach to predicting growth of *Nopalea cochenillifera* Giant Sweet clone submitted to water and saline stress

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ABSTRACT. Water and saline stresses are the main factors affecting agricultural production in semiarid regions. The tolerance of forage cactus to water and salt deficit makes it a promising solution, in particular *Nopalea cochenillifera*. The growth curves for species facing these conditions can provide useful information supporting the cultivation and management of natural populations and carry significant biological importance as growth rate assessment contributes to maintaining species viability. The objective of this study was to estimate the plant height and linear dimensions (length, width, and thickness) of *N. cochenillifera* Giant Sweet clone growing under water and saline stress. The experiment design was completely randomized, comprising a 4 × 4 factorial, with four water and four salinity levels; there were four replications. In order to estimate plant height in *N. cochenillifera* Giant Sweet clone as a function of the accumulated thermal sum, generalized additive models for location, scale, and shape (GAMLSS) were used to determine water level, saline level, length, width, and thickness. We constructed models using four distributions: the Weibull, Gumbel, Logistic, and Box-Cox power exponential distributions. The models were evaluated using global deviation and the generalized Akaike criterion. The Box-Cox power exponential proved to be the most effective in estimating *N. cochenillifera* height. This model enabled information relevant to practical environmental management to be obtained, as it precisely defined the optimum salt application and the required amount of replacement water, together with the cladode width for each plant growth stage using the accumulated thermal sum.

Keywords: forage cactus; BCPE model; plant height.

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Introduction

Species adapted to arid and semiarid environments, such as forage cactus (*Nopalea* spp. and *Opuntia* spp.), can contribute to increasing agricultural biomass yield by improving the utilization efficiency of local natural resources (Diniz et al., 2017). Cacti offer alternative forage in semiarid regions, due to their high phytomass production and energy values, the richness of their non-fibrous carbohydrate content, large water reserves, and ease of propagation (Freire et al., 2018).

Water deficit, a fairly common challenge in semiarid regions, causes changes in plant anatomy, physiology, and biochemistry, with consequent effects on all stages of development, growth, and productivity (Scalon, Mussury, Euzébio, Kodama, & Kissmann, 2011; Yahmed et al., 2016; El-Mageed, El-Samnoudi, Ibrahim, & Tawwab, 2018). Knowledge of how forage plants perform under water stress is therefore valuable to understanding the effect of the “dry” period on forage production, and therefore enabling the development of viable cultivation improvement practices (Araújo Jr. et al., 2019).

Water in semiarid regions contains high salt concentrations; water-stressed forage plants are therefore also exposed to salt stress (Silva, Jardim, Neto, Leite, & Teixeira, 2018). Salt accumulation in the soil is unfavorable to plant development because it negatively alters crop growth, thus reducing forage plant productivity in agricultural areas (Munns & Tester, 2008). Saline stress also promotes stomatal closure, which induces a reduction in CO₂ assimilation and consequently lowers levels of plant growth and biomass accumulation (Silva et al., 2018).

Forage cactus stands out as a promising solution to these difficulties, being tolerant of both water and salt deficit (Freire et al., 2018), with particular emphasis on the species *Nopalea cochenillifera* (L.) Salm-Dyck because it

is also resistant to the cochineal insect *Dactylopius opuntiae*. Further study of the development and growth of forage cactus under these conditions could therefore be productive. In this context, species growth curves can provide very useful and biologically important information about the cultivation and management of natural populations, as they enable species viability to be monitored through growth rate assessment. Growth curve adjustment is therefore an important tool in promoting an understanding of plant growth and phenological stages (Lucena, Prereira, & Leite, 2018a). Growth curves generate useful information supporting adequate crop management, such as the period of greatest plant growth, most suitable time for fertilization, and optimum pest control (Lucena et al., 2018a). For this purpose, a suitable measure of biological time is the accumulated thermal sum (ATS), which enables the effect of air temperature on plant growth and development to be simulated (Mendonça et al., 2012).

Generalized additive models for location, scale, and shape (GAMLSS) have proved very effective as a tool for adjusting growth curves and are especially suitable for modeling response variables that do not follow an exponential family distribution (e.g., leptokurtic or platykurtic distributions and/or with positive or negative asymmetry) (Rigby & Stasinopoulos, 2005). Response variables in GAMLSS follow any distribution (including continuous distributions with accentuated asymmetry or kurtosis, and discrete distributions).

No reports were found in the literature on the growth characteristics of *N. cochenillifera* in the presence of water and salt stress. The objective of this study was therefore to estimate the plant height and linear dimensions (length, width, thickness) of *N. cochenillifera* Giant Sweet clone in a water- and salt-stressed environment.

Material and methods

The research was carried out at the Federal Rural University of Pernambuco, Academic Unit of Serra Talhada (UFRPE/UAST), Brazil (elevation, 429 m; latitude, 7°56'15" S; longitude, 38°18'45" E). The climate is hot and dry (Köppen classification, BSwH), dominated by semiarid conditions with a rainy season during the summer (Leite, Lucena, Cruz, Sá Jr., & Simões, 2019). The average annual rainfall, air temperature, and relative humidity are 632.2 mm, 26°C, and 60%, respectively (Lucena, Leite, Simões, Simões, & Almeida, 2018b).

The soil used in the experiment (typical eutrophic Ta Haplic Cambisol) was collected from a depth of 0-20 cm, and then homogenized and sieved (2.0 mm). Analysis showed the soil to have the following chemical attributes: pH (water), 7.20; P (Mehlich I extractor), 40 mg dm⁻³; K⁺, 0.45; Ca²⁺, 5.3; Mg²⁺, 1.10; Al³⁺, 0.0 cmol_c dm⁻³.

The experimental design was a completely randomized 4×4 factorial, consisting of four levels of water replacement, based on crop evapotranspiration (ET_c) (25%, 50%, 75%, and 100% ET_c) and four levels of water salinity (0, 2, 4, and 8 dS m⁻¹), with four repetitions. Saline deficit conditions were created using four levels of irrigation water salinity, with different electrical conductivities. Sodium chloride (NaCl) salts were added to distilled water in the laboratory to achieve saline levels of 2, 4, and 8 dS m⁻¹, using (NaCl) salt concentrations corresponding to 1.16, 2.32, and 4.64 g L⁻¹, respectively.

Cladodes of forage cactus Giant Sweet clone were planted in pots (capacity, 14.41 dm³; 15 kg soil; one cladode per pot). Pots were arranged with a spacing of 0.3 × 0.3 m and placed on brick blocks to avoid direct contact with the underlying soil and facilitate the collection of drained water.

The following morphometric characteristics were evaluated: plant height (H), length (L), width (W), and thickness (T). Evaluations were carried out every 15 days, totaling 20 evaluations during the experimental period. Spearman's correlation was used to correlate the morphometric characteristics. The fittest models for predicting H in *N. cochenillifera* Giant Sweet clone as a function of the ATS, water level (WL), saline level (SL), L, W, and T were run using GAMLSS. ATS was defined as a function of the degree day (DD), using either the following equation:

$$DD = \frac{(T_{\max} + T_{\min})}{2} - T_b, \text{ se } T_{\min} > T_b$$

or

$$DD = \frac{(T_{\max} - T_b)^2}{2(T_{\max} - T_{\min})}, \text{ se } T_{\min} \leq T_b$$

and then

$$ATS = \sum_{i=1}^n DD_i$$

where T_{\max} and T_{\min} are the maximum and minimum daily temperatures, respectively, and T_b is the lower basal temperature.

Plants only begin development above T_b , which serves to activate plant metabolic responses (Renato, Silva, Sedyama, & Pereira, 2013). In our study, a T_b value of 22°C was established using the smallest mean error square and the highest model determination coefficient of the relationship between the total number of cladodes per plant and ATS.

GAMLSS is based on the premise that the response variable belonging to the exponential family is relaxed and replaced by a more general distribution family, D . The response variable y has a distribution of $D(y|\mu, \sigma, \nu, \tau)$, where $D \in D$ can be any distribution (including continuous distributions with accentuated asymmetry or kurtosis, and discrete distributions).

Rigby and Stasinopoulos (2005) proposed the GAMLSS approach, which assumes that the response variable y_i (with $i=1,2,\dots, n$) is independent of the probability density function $f(y_i|\theta^i)$, where $\theta^i=(\mu_i, \sigma_i, \nu_i, \tau_i)^T$ corresponds to the parameter vector. The first two elements μ_i and σ_i are the location and scale parameters, respectively; ν_i and τ_i are shape parameters.

The GAMLSS model is described as follows:

$$g_1(\mu) = \eta_1 = X_1\beta_1 + \sum_{j=1}^{J_1} Z_{j1} \gamma_{j1}$$

$$g_2(\sigma) = \eta_2 = X_2\beta_2 + \sum_{j=1}^{J_2} Z_{j2} \gamma_{j2}$$

$$g_3(\nu) = \eta_3 = X_3\beta_3 + \sum_{j=1}^{J_3} Z_{j3} \gamma_{j3}$$

$$g_4(\tau) = \eta_4 = X_4\beta_4 + \sum_{j=1}^{J_4} Z_{j4} \gamma_{j4}$$

where $g_k(\cdot)$ is a known monotonic link function for $k=1, 2, 3, 4$; μ, σ, ν, τ , and η_k are n -dimensional vectors; X_k represents known design matrices of order $n \times J_k$ associated with fixed effects β_k of $J_k \times 1$; and Z_{jk} signifies known design matrices of order $n \times q_{jk}$ associated with the random effects γ_{jk} of $q_{jk} \times 1$ with multivariate normal distribution. The quantity J_k represents the number of covariates used in the fixed effects of η_k , while J_k represents the number of random effects in η_k . A GAMLSS model can be described in matricial form as follows:

$$g_k(\theta^i) = \eta_k = X_k\beta_k + \sum_{j=1}^{J_k} Z_{jk} \gamma_{jk}$$

The best fit model for predicting H was defined using the Weibull, Gumbel, logistic, and Box–Cox power exponential (BCPE) distribution functions (Figure 1).

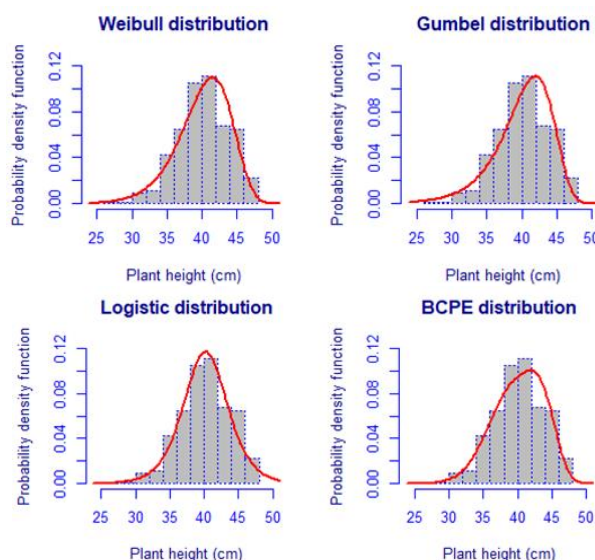


Figure 1. Histograms of the plant height of *N. cochenillifera* Giant Sweet clone in relation to probability density functions.

If there are Y_i random variables with a Weibull distribution of the parameters then the probability density function is given by

$\mu > 0$ and $\sigma > 0$,

$$f(y|\mu, \sigma) = \frac{\sigma y^{\sigma-1}}{\mu^\sigma} e^{-\left(\frac{y}{\mu}\right)^\sigma}$$

for

$y > 0, \mu > 0$ and $\sigma > 0$.

If there are Y_i random variables with a Gumbel distribution of the parameters, then the probability density function is given by

$-\infty < \mu < \infty$ and $\sigma > 0$

$$f(y|\mu, \sigma) = \frac{1}{\sigma} e^{-\left(\frac{y-\mu}{\sigma}\right)} e^{-\left(\frac{y-\mu}{\sigma}\right)}$$

for

$-\infty < y < \infty, -\infty < \mu < \infty$ and $\sigma > 0$.

If there are Y_i random variables with a logistic distribution of the parameters then the probability density function is given by:

$-\infty < \mu < \infty$ and $\sigma > 0$,

$$f(y|\mu, \sigma) = \frac{e^{\left(\frac{y-\mu}{\sigma}\right)}}{\sigma \left(1 + e^{-\left(\frac{y-\mu}{\sigma}\right)}\right)^2}$$

for

$-\infty < y < \infty, -\infty < \mu < \infty$ and $\sigma > 0$.

If there are Y_i random variables with a BCPE distribution of the parameters then the probability density function is given by:

$\mu > 0, \sigma > 0, -\infty < v < \infty$ and $\tau > 0$,

$$f(y|\mu, \sigma, v, \tau) = \frac{y^{v-1} \tau}{\mu^v \sigma} e^{\left(\frac{-0.5|z/c|^\tau}{2^{(1+1/\tau)} \Gamma(1/\tau) c}\right)}$$

where:

$$c = \left[2 \frac{2}{\tau} \frac{\Gamma\left(\frac{1}{\tau}\right)}{\Gamma\left(\frac{2}{\tau}\right)}\right]^{0.5}, \text{ and if } v \neq 0 \text{ } z = \frac{y^v - 1}{v\sigma} \text{ else } z = \log\left(\frac{y}{\mu}\right) / \sigma, \text{ for } y > 0, \mu > 0, \sigma > 0, -\infty < v < \infty \text{ and } \tau > 0.$$

Table 1 describes the link functions (η_k) for the probability distribution parameters used.

Table 1. Link functions (η_k) for the Gumbel, Weibull, logistic, and Box–Cox power exponential (BCPE) distributions.

Distribution	Link function			
	M	σ	v	τ
Gumbel	Identity $\eta_1 = \mu$	$\log \eta_2 = \log(\sigma)$	---	---
Weibull	$\log \eta_1 = \log(\mu)$	$\log \eta_2 = \log(\sigma)$	---	---
Logistic	Identity $\eta_1 = \mu$	$\log \eta_2 = \log(\sigma)$	---	---
BCPE	Identity $\eta_1 = \mu$	$\log \eta_2 = \log(\sigma)$	Identity $\eta_3 = v$	$\log \eta_4 = \log(\tau)$

μ , mean; σ , variance; v, asymmetry; τ , kurtosis

The models were evaluated using the following criteria: global deviation (GDEV) and generalized Akaike's information criterion (GAIC), as defined by Voudouris, Gilchrist, Rigby, Sedgwick, and Stasinopoulos (2012):

$$GDEV = -2l(\hat{\theta})$$

and

$$\text{GAIC}(k) = \text{GDEV} + (k + \text{df})$$

where $l(\hat{\theta})$ is the logarithm of the adjusted likelihood function, df denotes the effective total degrees of freedom of the model, and k is the penalty for each degree of freedom used. $\text{GAIC}(k)$ penalizes models with many parameters, such that, for any chosen value of k , the lower the $\text{GAIC}(k)$ value, the better adjusted is the model considered to be; $k = 2$ implies the Akaike information criterion (AIC), and $k = \ln(n)$ implies the Bayesian information criterion (BIC).

After defining the most appropriate model, a residue analysis was performed based on the quantile residues:

$$\hat{r}_i = \Phi^{-1}(\hat{u}_i)$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution and \hat{u}_i represents the quantile residues. The residues were also evaluated using a worm plot (Buuren & Fredriks, 2001). All analyses were performed using R-Project software version 2.13.1 (R Core Team, 2019) to adjust the models, and the `gamlss` package in the R software.

Results and discussion

Plant height showed positive asymmetric behavior, with a strong correlation with cladode length ($\rho = 0.85$) and width ($\rho = 0.80$) and a moderate correlation with cladode thickness ($\rho = 0.58$) (Figure 2).

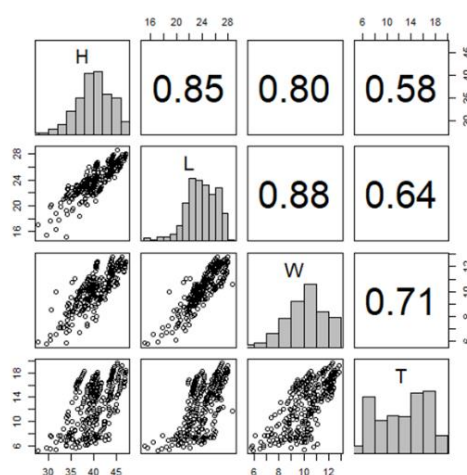


Figure 2. Correlations between morphometric measures (plant height (H), cladode length (L), cladode width (W), and cladode thickness (T)) of *N. cochenillifera* Giant Sweet clone.

The morphometric characteristics of forage cactus cladodes were positively correlated, as reported for *Nopalea cochenillifera* Little Sweet clone (Cunha et al., 2012), *Opuntia ficus-indica* (Reis, Gazarini, Fonseca, & Ribeiro, 2016; Guimarães, Donato, Azevedo, Aspiazú, & Silva Jr., 2018), and *Opuntia stricta* (Lucena et al., 2018b) as described in this study.

Table 2 describes the models adjusted for plant height as a function of the explanatory variables.

BCPE presented the best adequacy criteria (lower GDEV, AIC, and BIC) in relation to the other models, and was therefore confirmed as the most adequate model for explaining H as a function of the explanatory variables.

Recently, GAMLSS techniques have been applied to growth curve adjustment, as reported by Oliveira et al. (2020), who used a Skew-t type 3 (ST3) distribution, and Fumes, Demétrio, Villegas, Corrente, and Bazzo (2017), who used a Box-Cox normal (BCN) distribution to estimate height of *Eucalyptus* species. However, our literature search found no reports of using GAMLSS for modeling in pasture and forage studies; instead, response variable modeling has been evaluated using only simple or multiple linear regression models (Reis et al., 2016; Freitas et al., 2018), or generalized linear models (Lucena et al., 2018b). These modeling techniques do not yield information about asymmetry and kurtosis parameters, whereas GAMLSS does this

very well. This was supported by our study, in which most response variables, such as H, presented leptokurtic or platykurtic distributions and/or with positive or negative asymmetry. GAMLSS was therefore more efficient for modeling these types of response variable, because they are not captured by other models.

Table 2. Estimated parameters for the Gumbel, Weibull, logistic, and Box–Cox power exponential (BCPE) models.

	Estimate	Standard error	t-value	p-value	Criteria for goodness of fit models		
					GDEV	AIC	BIC
Gumbel							
μ model							
ATS	-0.0067	0.0006	-10.96	<0.001	1491.58	1501.58	1519.89
WL	0.0237	0.0058	4.08	<0.001			
SL	0.6885	0.0522	13.18	<0.001			
W	4.2191	0.0645	65.35	<0.001			
log (σ) model							
Intercept	1.0266	0.0454	22.63	<0.001			
Weibull							
log (μ) model							
Intercept	3.267	0.0325	100.32	<0.001	1268.06	1280.06	1302.04
ATS	-0.00002	0.00001	-1.99	0.047			
WL	-0.0005	0.00001	-4.87	<0.001			
SL	-0.0021	0.0009	1.42	0.043			
W	0.048	0.0033	14.71	<0.001			
log (σ) model							
Intercept	3.067	0.0472	64.98	<0.001			
Logistic							
μ model							
ATS	-0.0052	0.0007	-7.49	<0.001	1484.50	1494.50	1512.82
WL	0.0302	0.0057	5.29	<0.001			
SL	0.2869	0.0669	4.29	<0.001			
W	4.0539	0.0671	60.38	<0.001			
log (σ) model							
Intercept	0.5694	0.0499	11.41	<0.001			
BCPE							
μ model							
Intercept	21.7652	1.2243	17.77	<0.001	1248.33	1264.33	1293.63
ATS	-0.0019	0.0007	-2.99	0.003			
WL	-0.0159	0.0047	-3.39	<0.001			
SL	0.2459	0.0735	3.35	<0.001			
W	2.0115	0.1249	16.10	<0.001			
log (σ) model							
Intercept	-2.9766	0.0435	-68.36	<0.001			
v model							
Intercept	7.7870	1.1010	7.07	<0.001			
log (τ) model							
Intercept	1.7323	0.2946	5.88	<0.001			

GDEV, global deviation; AIC, Akaike's information criterion; BIC, Bayesian information criterion; ATS, accumulated thermal sum; WL, water level; SL, saline level; W, width.

Amador, Avila, Diéguez, Garibay, and Jones (2001) verified that values for *O. ficus-indica* cladode numbers, L, and W reduce with increasing salinity levels in the irrigation water. Queiroz et al. (2015) reported that plant H and cladode L, W, T, and numbers are affected by increases in the percentage of reference ETc. Freitas et al. (2018) used salinity level and irrigation frequency as variables, and found that both minimized growth in cladodes of *N. cochenillifera* Little Sweet clone. Lucena et al. (2018a) used the number of days and cladode W to explain growth in *N. cochenillifera* Giant Sweet clone, confirming that cladode W increased with increasing plant H; this is the same behavior presented in our study.

The BCPE model was considered to be well adjusted because quantile residues were within the limits of ± 3 (Figure 3a) and theoretical quantiles closely followed the BCPE distribution (Figure 3b), with no inadequacy in the response variable distribution; the same behavior was reported by Fumes et al. (2017) and Oliveira et al. (2020) in their evaluation of *Eucalyptus* height.

A worm plot (Figure 4) was constructed and showed that all points were within the confidence bands; this therefore also demonstrated the adequacy of the BCPE model to explain plant H in *N. cochenillifera*.

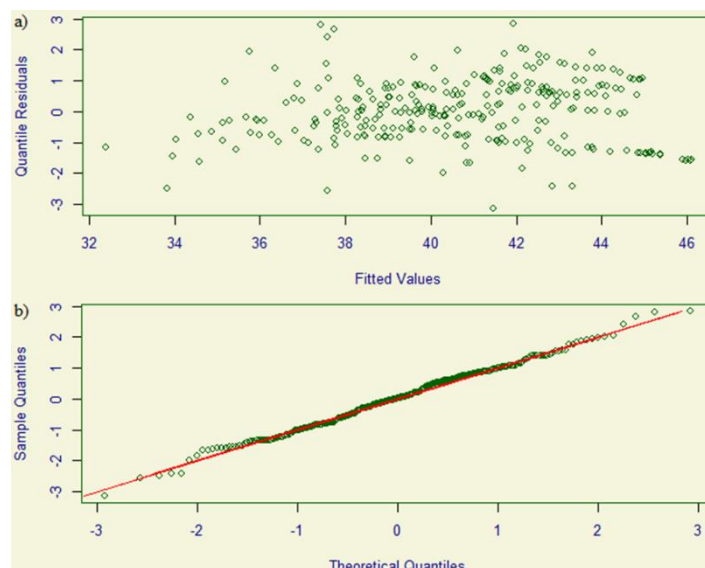


Figure 3. Fitted values (a) and quantile–quantile theoretical distribution (b) for residuals of the Box–Cox power exponential model.

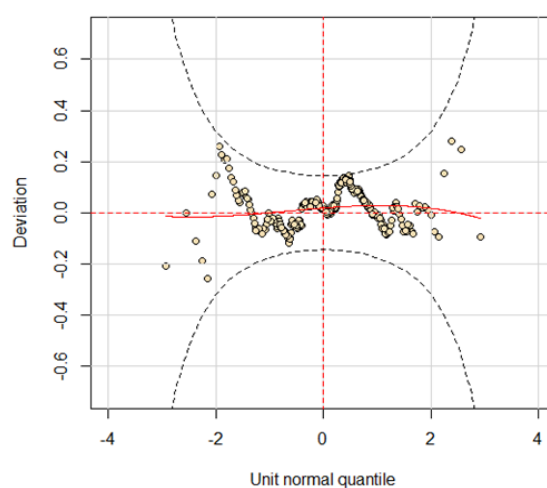


Figure 4. Worm plot of the residuals of the Box–Cox power exponential model.

Conclusion

Adjustment of the BCPE model yielded information relevant to practical management, because the method allowed the optimum salt and water replacement quantities to be precisely defined. This in turn enabled cladode width for each plant growth phase to be determined using the ATS, thus maximizing plant growth at each phenological stage, resulting in greater dry mass production.

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