Programa de Pós-Graduação em Produção Vegetal no Semiárido

PREDIÇÃO DE COLHEITA E ESTIMATIVAS DO TAMANHO E FORMATO DE PARCELAS EXPERIMENTAIS PARA PALMA FORRAGEIRA 'GIGANTE'

BRUNO VINÍCIUS CASTRO GUIMARÃES

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Tese apresentada à Universidade Estadual de Montes Claros, como parte das exigências do Programa de Pós-Graduação em Produção Vegetal no Semiárido, área de concentração em Produção Vegetal, para obtenção do título de Doutor.

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Prof. Dr. Ignacio Aspiazú

Janaúba
2020

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APROVADA em 30 de março de 2020.

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Aos meus pais, que por todas suas vidas renunciaram e abdicaram do essencial para oferecer a máxima oportunidade aos seus filhos, ensinando-os o verdadeiro sentido de viver, persistir e prosperar o bem;

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Dedico.

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BIOGRAFIA

Bruno Vinícius Castro Guimarães, filho de Marconde Teixeira Guimarães e Luzia do Socorro Castro, nasceu no município de Guanambi, Bahia, aos 20 de março de 1984. Nessa cidade, iniciou seus estudos primários na Unidade Escolar Padre Manoel da Nóbrega, concluindo o ensino fundamental no Colégio Estadual Governador Luiz Viana Filho em 1998. Cursou o ensino médio no Colégio Modelo Luís Eduardo Magalhães, entre 1999 e 2001.

Nesse mesmo ano, iniciou o curso Técnico em Agropecuária na Escola Agrotécnica Federal de Guanambi - BA, concluindo-o em 2002. Em 2004, ingressou na Universidade Estadual do Sudoeste da Bahia - UESB, na qual, desde o segundo ano de graduação atuou como estagiário voluntário do laboratório de Biotecnologia e bolsista do laboratório de Tecnologia e Produção de Sementes pela Fundação de Amparo à Pesquisa do Estado da Bahia - FAPESB, alcançando o diploma de Engenheiro Agrônomo no ano 2008. Ainda no ano 2008 foi aprovado, em primeiro lugar, como aluno especial do mestrado em Fitotecnia da Universidade Estadual do Sudoeste da Bahia - UESB. Concomitantemente, iniciou as atividades de consultoria em empresa privada, fiscalização de projetos do Programa Nacional de Fortalecimento da Agricultura Familiar - PRONAF, professor colaborador do Centro de Educação Tecnológica do Estado da Bahia - CETEB e docente na Escola Família Agrícola de Caculé - BA. No ano posterior, 2009, foi aprovado, em primeiro lugar, como professor substituto do Instituto Federal Baiano, campus Guanambi, sendo que, nesse mesmo ano, alcançou aprovação pelo programa de mestrado em Produção Vegetal no Semiárido pela Universidade Estadual de Montes Claros - UNIMONTES, também na primeira colocação. Ainda nesse ano de 2009, conseguiu a classificação em vários concursos públicos na área de Ciências Agrárias, a citar, EMBRAPA, CODEVASF, IDENE, IFNMG, IFBAIANO e IFAM, sendo o ingresso, neste último órgão, com dedicação efetiva.

Entre 2010 e 2013, atuou como tutor presencial do programa de formação de professores em Ciências Biológicas pela Universidade Federal do Amazonas – UFAM. Nesse mesmo período, foi designado como consultor e responsável técnico pelo projeto Diagnóstico Etnoambiental, Segurança Alimentar e Alternativas Econômicas para os Hupdäh, desenvolvido no extremo noroeste do Amazonas em parceria com a Organização Não Governamental Saúde Sem Limites - SSL e o Instituto Federal do Amazonas - IFAM. Em 2011, defendeu o mestrado, obtendo a aprovação com louvor. Entre 2013, atuou como supervisor dos cursos de Formação

Inicial Continuada - FIC do Programa Nacional de Acesso ao Ensino Técnico e Emprego – PRONATEC, sendo que, nos anos posteriores, 2014 e 2015, foi nomeado coordenador adjunto do programa, promovendo a capacitação de aproximadamente 900 profissionais em diversas áreas do conhecimento. Em 2015, ingressou no programa de doutorado em Produção Vegetal no Semiárido pela UNIMONTES, com aprovação em primeiro lugar. Em março de 2020, defendeu a tese estruturada em 10 capítulos/artigos, sendo a maior parte deles publicados em revistas especializadas antes mesmo da defesa.

Ainda no mês de março de 2020, foi selecionado pelo programa de pós-doutoramento da Universidade Estadual de Montes Claros – UNIMONTES para dar continuidade aos estudos do projeto acadêmico profissional com a palma forrageira.

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RESUMO GERAL

GUIMARÃES, Bruno Vinícius Castro. **Predição de colheita e estimativas do tamanho e formato de parcelas experimentais para palma forrageira 'Gigante'.** 2020. 216p. Tese (Doutorado) - Universidade Estadual de Montes Claros, Janaúba. Orientador: Ignacio Aspiazú. Coorientador: Sérgio Luiz Rodrigues Donato - IFBaiano - *Campus* Guanambi.

Dentre as forrageiras, a palma 'Gigante', *Opuntia ficus-indica* Mill, destaca-se, sobretudo no ecossistema semiárido, pela alta resiliência às condições adversas associada à máxima produção de biomassa vegetal. Por essa singular importância no campo da agropecuária, diversos estudos têm sido desenvolvidos em busca do maior entendimento e pressuposições agronômicas sobre essa variedade. Entre eles, destacam-se a predição de colheita e a definição do tamanho da parcela experimental, para propiciar extrapolação segura de resultados. Dessa forma, objetivou-se com este trabalho construir modelos para predição da colheita e estimar o tamanho e o formato de parcelas para avaliação fenotípica da palma forrageira 'Gigante'. O experimento de campo foi desenvolvido na condição de sequeiro na área experimental do Instituto Federal Baiano, a partir de um ensaio em branco ou com ausência de tratamentos, em que, nas etapas de preparo do solo, adotou-se um padrão de uniformidade em toda a área experimental. Simultaneamente, procederam-se com a seleção dos cladódios e o devido preparo destes para o plantio, com tempo de cura de 15 dias à sombra. A adubação orgânica foi realizada em três aplicações, sendo 60 Mg ha^{-1} ano^{-1} de esterco de ovino no primeiro ano, parcelados em 30 Mg ha^{-1} no sulco na ocasião do plantio e 30 Mg ha^{-1} em cobertura após o enraizamento das plantas, posteriormente, no segundo ano de plantio, correspondente aos 360 DAP, realizou-se uma nova aplicação com 60 Mg ha^{-1} a lanço nas entrelinhas, repetindo a mesma dosagem de 60 Mg ha^{-1} aos 720 DAP. Práticas agronômicas complementares foram realizadas com base nas recomendações para a cultura forrageira. Com isso, as plantas, denominadas como unidades básicas UB, foram submetidas aos mesmos tratos culturais e à mesma sistematização de plantio com 2,0 x 0,2 m, em um arranjo de 10 fileiras com 50 plantas cada, sendo consideradas como parcela útil o gride i x j com i = 48 linhas e j = 8 colunas, correspondentes a 384 UBs numa área total com 153,60 m^2. Aos 930 DAP, avaliaram-se os descritores morfológicos, altura da planta; comprimento, largura, espessura, área e número dos cladódios; massa dos cladódios e área total do cladódio no terceiro ciclo de produção. Para cada característica vegetativa estudada, objeto da

avaliação das 384 UB, foram combinados diversos tamanhos de parcelas que permitissem o preenchimento de toda a área experimental. Desse modo, foram contemplados 15 diferentes tamanhos de parcelas pré-estabelecidos com formatos retangulares e em fileiras. A predição da colheita foi realizada por Redes Neurais Artificiais – RNA e pelos modelos de interface da análise de regressão simples, múltipla, quadrática e interação. O tamanho das parcelas foi estimado pelos métodos da máxima curvatura modificada, tamanho conveniente de parcela, linear e quadrático com resposta a platô, comparação de variâncias e a informação relativa. Para predição da colheita, foram ajustadas redes neurais artificiais com coeficiente de determinação de 0,87 para a amostra de validação, assegurando o potencial de generalização do modelo. Os caracteres morfológicos de maior contribuição relativa foram a área total do cladódio, altura da planta, espessura do cladódio e comprimento do cladódio, porém, todos são importantes na predição da produtividade. Por meio da regressão linear múltipla, interação quadrática com todas as variáveis ou somente a característica área total do cladódio para a regressão linear simples, foi possível estimar a produtividade da palma forrageira no semiárido nordestino como aporte nutricional e hídrico para fomentar o planejamento rural. No tocante à determinação dos tamanhos de parcelas, o modelo da máxima curvatura modificado estimou tamanhos de parcela entre três e nove plantas no sentido da fileira de cultivo para as características em estudo. Estimativas de diferentes tamanhos de parcelas foram construídas pela metodologia matricial proposta por Hatheway, em que o pesquisador pode fazer uso de uma série de combinação entre os parâmetros, número de tratamento, número de repetições, diferença a ser detectável e o coeficiente de variação da característica para selecionar o tamanho conveniente da parcela. Os estimadores de regressão linear e quadrático com resposta platô determinaram parcelas com 10 e 17 unidades básicas, respectivamente. Pelo método da comparação de variância, considerou-se como tamanho ótimo parcelas com 12 UB (4,8 m²), pois o emprego de tamanhos superiores não diminui significativamente a variância. O tamanho e o formato de parcela mais adequados foram determinados pela maior informação relativa associada ao menor coeficiente de variação. Estudos com a palma forrageira ‘Gigante’ têm sido desenvolvidos com tamanhos de parcelas diversificados com 15, 32 e 36 unidades básicas. Contudo, em consonância com os resultados obtidos nesse trabalho, a área experimental pode ser otimizada com redução significativa no tamanho e formato da parcela. O tamanho da parcela experimental com oito unidades básicas no formato com oito colunas e uma planta por coluna assegura eficiência na avaliação

experimental, pois essa combinação entre tamanho e formato, além de atender todas as características normalmente avaliadas em estudos com a palma forrageira, tem-se o máximo controle da heterogeneidade do solo, com a diminuição do erro experimental e ganhos significativos sobre a precisão. Adicionalmente, a partir dos caracteres morfológicos, é possível predizer a produção de palma forrageira com alta precisão por meio das RNAs e dos modelos de regressão.

Palavras-chave: *Opuntia ficus-indica,* modelos, métodos, ensaio, caracteres morfológicos, precisão experimental.

GENERAL ABSTRACT

GUIMARÃES, Bruno Vinícius Castro. **Harvest prediction and estimates of the size and shape of experimental plots for 'Gigante' Cactus Pear.** 2020. 225p. Thesis (Doctor's Degree in Plant Production in Semiarid) - Universidade Estadual de Montes Claros, Janaúba-MG. Advisor: Ignacio Aspiazú. Co-Advisor: Sérgio Luiz Rodrigues Donato - IFBaiano - *Campus* Guanambi.

Among the forage crops, 'Gigante' cactus pear (*Opuntia ficus-indica* Mill) stands out, especially in the semiarid, for its high resilience to adverse conditions associated with high biomass production. Due to its unique importance in agriculture, several studies have been developed in search of greater understanding and agronomic assumptions about this cactus variety. Predicting harvest and defining the experimental plot size are important to safely extrapolate research results. Thus, the objective of this work was to build harvest-predicting models to estimate the size and shape of plots for phenotypic evaluation of the 'Gigante' forage cactus pear. The field experiment was carried out under rainfed condition in the experimental area of the Federal Institute of Bahia. A blank test, that is, with no treatments, was conducted, in which the soil was evenly prepared throughout the experimental area. The cladodes used for planting were selected and cured for five days in shade. Organic fertilizers were applied three times at a rate of 60 Mg ha-1 year-1 of sheep manure in the first year: 30 Mg ha-1 in the planting furrow and 30 Mg ha-1 as top dressing after rooting of the plants. In the second year, which corresponded to 360 days after planting (DAP), a new application was carried out with 60 Mg ha-1 between rows, repeating the same rate of 60 Mg ha-1 at 720 DAP. Other crop practices were done based on recommendations for forage crops. Therefore, the plants, each considered a basic unit (BU), were subjected to the same crop practices and planted at the same spacing of 2.0 x 0.2 m. The plants were arranged into 10 rows containing 50 plants each. Following the grid i x j, 384 plants or BUs arranged in i = 48 rows and j = 8 columns were considered for measurements, for a total area of 153.60 m². At 930 DAP, the following morphological descriptors were measured in the third production cycle: plant height, cladode length, cladode width, cladode thickness, cladode area, number of cladodes, weight of cladodes, and total area of cladodes. For each vegetative characteristic measured in the 384 BUs, several sizes of plots were combined so that the plants would fill the whole experimental are. Thus, 15 different sizes of pre-established rectangular-shaped plots and rows were used. Harvest prediction was performed by Artificial Neural Networks (ANN) and by the interface

models of simple, multiple, quadratic and interaction regression analysis. Plot sizes were estimated by the methods: modified maximum curvature, convenient plot size, linear and quadratic response plateau, comparison of variances and relative information. To predict the harvest, artificial neural networks with a coefficient of determination of 0.87 were fitted for validating the sample, which ensured the potential of generalization of the model. The morphological characters that had the greatest relative contribution were total area of the cladode, plant height, cladode thickness, and cladode length; however, all traits measured are important for predicting cactus pear yield. Through multiple linear regression, quadratic interaction across all variables or simple linear regression for total cladode area, it was possible to estimate the yield of forage cactus pear grown in Brazilian northeastern semiarid as nutritional and water resource for livestock. Regarding the determination of plot sizes, the modified maximum curvature model estimated plot sizes between three and nine plants in the direction of the plant row for the characteristics studied. Estimates of different plot sizes were built using the matrix methodology proposed by Hatheway, in which the investigator can make use of a series of combinations between parameters, number of treatment, number of replicates, difference to be detected and the coefficient of variation of the characteristic to select the convenient plot size. The linear and quadratic regression with plateau response methods determined plots with 10 and 17 basic units, respectively. By the method of comparison of variance, plots with 12 BUs (4.8 m²) were the optimum size since the use of larger sizes does not significantly decrease the variance. The most suitable plot size and shape was determined by the greater relative information associated with the lower coefficient of variation. Studies on 'Gigante' forage cactus pear have been conducted using plot sizes having 15, 32 and 36 basic units; however, based on the results of this work, the experimental area can be optimized by significantly reducing the size and shape of the plot. An experimental plot with eight basic units arranged in eight columns composed of one plant each ensures efficiency during the experimental evaluation. This combination of size and shape has the highest control of soil heterogeneity in addition to meeting all the characteristics normally evaluated in studies with forage cactus pear. Furthermore, reduction in experimental error and significant gains in accuracy are expected. From the morphological characters, one can predict the yield of forage cactus pear with high precision using ANNs and regression models.
Keywords: *Opuntia ficus-indica,* models, methods, assay, morphological characters, experimental precision.

INTRODUÇÃO GERAL

Importância da palma forrageira para o semiárido

A palma ‘Gigante’ (*Opuntia ficus-indica* Mill) é uma forrageira com classificação botânica pertencente à família das cactáceas (TAIZ et al., 2017). A espécie supracitada, foco deste trabalho, apresenta plantas de porte bem desenvolvido com caule pouco ramificado, o que lhes transmite um aspecto mais ereto e crescimento vertical compacto. Sua raquete, oval-elíptica, não possui espinhos e tem massa úmida equivalente a um kg e comprimento de até 50 cm (SILVA et al., 2015). Essa espécie, por apresentar atributos morfofisiológicos de adaptação à limitação hídrica do solo, é considerada a mais produtiva e mais resistente às regiões secas, as raquetes são revestidas por uma cutícula que controla a transpiração, permitindo a manutenção da água no tecido vegetal entre 90 e 93% (MARQUES et al., 2017); no entanto, é menos palatável e de menor valor nutricional, quando comparada com a palma redonda (*Opuntia* sp.) e a palma miúda (*Nopalea cochenilifera* (L.) Salm Dyck).

A palma não tolera umidade excessiva e, em solos profundos, apresentam estruturas radiciais eficientes na extração e armazenamento da água. Além disso, o metabolismo fotossintético CAM, Crasssulacean Acid Metabolism, permite às cactáceas maiores eficiências na conversão energética, uma vez que os estômatos permanecem fechados no período diurno, para evitar a perda excessiva de água, e abertos durante o período noturno, para absorção do CO_2, esses mecanismos de adaptação favorecem maior interação da cultura com a região semiárida (TAIZ et al., 2017).

A palma forrageira tem como centro de origem, domesticação e diversidade genética a América Central, possivelmente, a região do México (REYES-AGUERO et al., 2005). No Brasil, a cultura foi incorporada com ampla utilidade na alimentação animal em diversas regiões áridas e semiáridas do território nacional (MOURA et al., 2011). No Nordeste brasileiro, a palma é considerada uma fonte energética com grande potencial na nutrição e manutenção de ruminantes (OLIVEIRA et al., 2010). Na Bahia, a cultura tem sido utilizada predominantemente nas áreas de sequeiro nos municípios situados no semiárido (ALMEIDA, 2011). Estudos contemporâneos apontam a palma como recurso alimentar estratégico e de alto desempenho na dieta de novilhas leiteiras no Sudoeste baiano (AGUIAR et al., 2015a; AGUIAR et al., 2015b).

A palma forrageira configura-se como alternativa, entre as cactáceas, com maior potencial de adaptação às condições adversas do semiárido e exploração agronômica no

Nordeste, constituindo-se em importante recurso forrageiro nos períodos de estiagens, devido ao seu elevado potencial de produção de biomassa. Além do expressivo valor nutritivo, resistência à seca, eficiência de uso de água e rusticidade, a cultura é amplamente incorporada aos arranjos produtivos do sertão (LÉDO et al., 2019).

Nesse contexto, o cultivo dessa forrageira tem sido ampliado em vários estados do Nordeste e, de modo recente, o território baiano tem intensificado os trabalhos sobre pesquisa e produção de palma (BRITO et al., 2018; FONSECA et al., 2019; TEIXEIRA et al., 2019; ALVES ET AL., 2019a, 2019b; GUIMARÃES et al., 2020; LÉDO et al., 2020). Contudo, o sistema agrícola da região ainda é caracterizado como inconsistente e de nível tecnológico baixo, o que favorece produtividade inferior ao potencial da cultura, conforme argumentam Silva et al. (2012).

Em face da grande importância da palma e do reconhecimento da maioria dos pecuaristas do semiárido, o Brasil ocupa a maior área plantada do mundo, estima-se 600 mil ha cultivados predominantemente com a palma gigante, todavia, a produtividade é precária e pouco expressiva, sendo, muitas vezes, insuficiente para atender a demanda do rebanho local, em torno de 40 t ha^{-1}. Por outro lado, no México, centro de origem da cultura, os produtores alcançam patamares de produção de 400 t de matéria verde ha^{-1} (MARCONATO, 2008), fato que evidencia o potencial produtivo da palma gigante.

Ainda no tocante à capacidade produtiva da cultura, cabe ressaltar que o desempenho agronômico da cultura é influenciado por inúmeros aspectos, tais como: condições climáticas, qualidade do solo, tamanho da propriedade, oferta de mão de obra, assistência técnica, possibilidade de mecanização, custos de aquisição de insumos, disponibilidade de adubo orgânico, níveis e fontes dos adubos, controle de plantas invasoras, pragas e doenças, cultivo consorciado ou solteiro e espaçamento utilizado, conforme argumentam Dubeux Júnior et al. (2010).

Dentre os fatores de produção supracitados, Donato et al. (2017a, 2017b) evidenciaram que o incremento de adubação orgânica ao solo (esterco bovino) influenciou, de forma crescente, o teor de proteína bruta, nitrogênio total, proteína de rápida e intermediária degradação em forragem de palma. Nesse cenário, Oliveira et al. (2010) corroboram sobre o potencial produtivo da cultura quando submetida ao manejo adequado dos insumos agrícolas. Estudos desenvolvidos no contexto semiárido adicionam que o uso de fertilizantes químicos (SILVA et al., 2012) ou orgânicos (DONATO et al., 2014a; BARROS et al., 2016), níveis de adubação (DUBEUX JÚNIOR et al., 2010; PADILHA JÚNIOR et al., 2016), arranjo espacial de plantio (DONATO et al., 2014b; DONATO et al., 2016), irrigação (SANTOS et al., 2020) e manejo correto da colheita (SILVA et al., 2012) têm alcançado incremento significativo na produção de matéria seca em palma forrageira.

Contudo, os estudos em questão, apesar da grande relevância para a região, retratam discrepância acerca do arranjo experimental empregado, resultando em desuniformidade na unidade experimental. Assim, entre os padrões tecnológicos para obter resultados mais eficientes no universo da palma, tem-se como pilar e marco inicial a fundamentação das pesquisas agrícolas para subsidiar e dar suporte ao pesquisador sobre o tamanho, forma da parcela experimental e repetições utilizadas com a finalidade de se encontrar a menor unidade básica de representação agronômica da cultura.

Tamanho e forma da parcela ou unidade experimental

O tamanho ideal da parcela experimental apresenta correlação específica entre a causa e o efeito, sendo consideradas inúmeras variáveis para o dimensionamento da parcela, tais como: índice de heterogeneidade do solo (STORCK et al., 2005), material genético (STORCK et al., 2011), equilíbrio entre precisão e custos (GUARÇONI et al., 2017), natureza do material experimental, delineamento utilizado, número de repetições e métodos de avaliação (CARGNELUTTI FILHO et al., 2018).

Para o sucesso numa unidade de pesquisa experimental, é de fundamental importância que unidades de avaliação sejam capazes de detectar variações cada vez menores visto que a tendência se resume ao fato de que as diferenças entre as novas cultivares diminuam; por este motivo, o desafio do pesquisador está em maximizar a precisão experimental, o que possibilitará resultados mais fidedignos e expressivos do desempenho agrícola e, por conseguinte, a seleção de materiais mais produtivos, mais adaptados e de melhor qualidade. Todavia, para a implantação de experimentos com significativa precisão é necessário um planejamento adequado e, nesse universo da pesquisa, uma das questões básicas sempre presentes nos experimentos diz respeito ao tamanho e a forma apropriada da parcela (SOUSA et al., 2015).

Estimativas do tamanho ótimo de parcela e do número de repetições para experimentos com palma forrageira são escassas na literatura, fato que dificulta e, por vezes, inviabiliza a padronização da unidade experimental e, por conseguinte, a otimização dos recursos empregados, além da possibilidade de incorrer em resultados discrepantes do ponto de vista científico ou fora do viés da estatística.

As unidades básicas experimentais são planejadas com o intuito de detectar diferenças significativas entre tratamentos testados, o que depende da precisão experimental. Esta, por sua vez, sofre interferência de inúmeros fatores, tais como: tamanho e forma de parcelas, forma de bloco, número de repetições, delineamento experimental, falhas de plantas nas parcelas e forma de condução do experimento, conforme argumentam Donato et al. (2008). Nesse cenário, o pesquisador acrescenta que a área - tamanho e a forma - dimensões da parcela experimental, bem como o número de repetições, compõem necessidades práticas quando se planejam ensaios experimentais (CARGNELUTTI FILHO et al., 2018). Assim, a precisão experimental, tão almejada na pesquisa aplicada, depende da caracterização adequada dos moldes determinados nas unidades básicas de avaliação.

Os estudos pioneiros sobre a estimativa de tamanho de parcelas experimentais para a triticultura foram propostos por Wiebe (1935). Com base nos dados e ensaios de uniformidade, Smith (1938) idealizou o método do índice de heterogeneidade do solo, precursor de vários métodos para a mesma cultura. Gomez & Gomez (1984) afirmam que a seleção do tamanho da parcela tem como condição principal o grau de heterogeneidade do solo.

Muniz et al. (1999) enfatizam que o desempenho agronômico de um tratamento em parcelas experimentais, associado com a margem de erro experimental, correlaciona diretamente com o índice de heterogeneidade do solo. Essa disparidade do solo pode ser estimada por meio de ensaios de uniformidade, em que toda a área experimental é implantada com uma única variedade homogênea, utilizando-se tratos culturais idênticos de cultivo. Para Lorentz et al. (2012), a heterogeneidade do solo é considerada a fonte mais importante da variação em experimentos de campo, mas acrescentam que variabilidade genética do material experimental também contribui para a precisão experimental.

Não obstante, a relação entre o tamanho da parcela e o número de repetições no intuito de minimizar o erro experimental deve ser maior em plantas de propagação sexuada de polinização cruzada – com expressivo grau de alogamias, por apresentarem maior variabilidade genética quando comparadas a culturas autógamas e plantas de propagação assexuada, pois, nestas, ocorrem maior uniformidade genética (ROSSETTI, 2002).

O tamanho adequado da parcela experimental deve culminar aspectos práticos, homogeneidade do material genético, número de tratamentos por bloco, unidades dentro da parcela experimental e os custos por parcela (FEDERER, 1963). Contudo, o grau de heterogeneidade do solo tem sido considerado como uma das medidas mais úteis da variabilidade do solo (LORENTZ et al., 2012) e a variável principal na estimativa do tamanho de parcela (BERTOLUCCI et al., 1991).

Na ocasião em que o desempenho agronômico de parcelas adjacentes apresentar diferenças mínimas significativas, o fator de variação é atribuído à heterogeneidade do solo (LORENTZ et al., 2012; GOMEZ & GOMEZ, 1984) que, associada à variabilidade genética do material experimental, influencia diretamente o número de repetições e o tamanho da parcela experimental utilizada (DONATO et al., 2008).

Storck et al. (2005) delineiam que a heterogeneidade dos solos experimentais é decorrente de diversos fatores e diferentes níveis de intensidade, tais como: fertilidade, drenagem, relevo, manejo ou resíduos de culturas anteriores, aplicação de fertilizantes. Assim, a magnitude do erro experimental pode estar relacionada com a variabilidade genética experimental, as competições intra e interparcelar e a disparidade do solo.

O tamanho ideal da parcela ou unidade experimental deve estabelecer um equilíbro entre o erro e a precisão experimental, uma vez que a relação entre tamanho da parcela e erro experimental é inversamente proporcional (SMITH, 1938; LORENTZ et al., 2012), entretanto, a maior dimensão das parcelas está associada ao maior custo (GUARÇONI et al., 2017). Além disso, o acréscimo da precisão é limitado quando a parcela se torna muito extensa (GOMEZ & GOMEZ, 1984), e o ganho na precisão decresce com a expansão demasiada na área das parcelas (BANZATTO & KRONKA, 1995).

Na unidade experimental, o acréscimo da área das parcelas limita o número de repetições, o inverso é verdadeiro, embora isso não deve ser proporcional, pois, segundo Ferreira (2000), é recomendável minimizar a área da parcela em prol do expressivo número de repetições, uma vez que este assegura a maior possibilidade de aferir a precisão experimental. Contudo, quando o número de repetições requerido se torna muito elevado, são necessárias outras formas de aumentar a precisão, como alterações no tamanho da parcela (LIN, BINNS, 1984).

Assim, as unidades experimentais são associadas inevitavelmente ao material genético e à heterogeneidade dos solos, o que estabelece características bastante peculiares, em que, por vezes, parcelas menores são adequadas, enquanto, em outras condições, parcelas grandes são indispensáveis, porém, com menor repetição (CORDEIRO, MIRANDA, 1983). Todavia, inúmeros autores corroboram que a maior precisão experimental é alcançada utilizando-se maior número de repetições de parcelas menores (LORENTZ et al., 2012). Em estudos com culturas específicas, Cargnelutti Filho et al. (2014), Cargnelutti Filho et al. (2012), Henriques Neto (2003), Storck et al. (2005), Paranaíba et al., (2009a; 2009b), Oliveira et al. (2014) relataram que as parcelas menores foram mais precisas e eficientes que as parcelas maiores para as culturas do feijão, milho, trigo, batata, mandioca e banana, nessa ordem.

Esses resultados asseguram o significativo efeito do número de repetições sobre a precisão experimental. Contudo, a adoção dessa relação no intuito de diminuir o erro experimental em alguns casos, dependendo do número de tratamentos, do delineamento e do tamanho da parcela, pode levar a tamanhos de experimentos impraticáveis (HENRIQUES NETO, 2003).

De acordo com Ferreira (2000), as dimensões das parcelas, em formato retangular utilizado em delineamentos em blocos casualizados ou quadrático para delineamentos em quadrado latino, exercem influência mais significativa em parcelas maiores que em parcelas menores, com reflexo positivo na redução do erro experimental. Contudo, Bertolucci et al. (1991) encontraram em seus estudos melhor precisão experimental para parcelas quadradas. Por outro lado, a parcela mais adequada é aquela que permite o maior controle das condições acidentais adversas e que se adeque aos tratamentos do estudo (DONATO et al., 2008).

Para Ortiz (1995), a utilização de parcelas em fileiras torna-se muito importante em solos heterogêneos ou quando o gradiente do solo ocorre perpendicular à fileira. Nessas circunstâncias, variações nas parcelas podem decrescer significativamente tanto quanto as parcelas tornarem-se extensas e estreitas.

Para Donato et al. (2018), o tamanho e a forma da parcela interferem na precisão experimental e, por conseguinte, auferem resultados mais precisos e possibilitam detectar diferenças estatísticas significativas entre os tratamentos testados. Assim, a estatística requer tais informações para alcançar o fim a que se destina: a precisão experimental.

Nesse cenário, a estimativa de tamanho, a forma das parcelas experimentais e o número de repetições requeridas, para detectar diferenças mínimas significativas entre médias de tratamentos quando se consideram diversas culturas e diferentes métodos, são bastante expressivos. Entre os inúmeros trabalhos desenvolvidos no Brasil e no exterior, vale citar, com abobrinha (CARPES et al., 2010), alface (LÚCIO et al., 2011), arroz (PARANAÍBA et al., 2009a), arroz irrigado (CARGNELUTTI FILHO et al., 2012), aveia (CARGNELUTTI FILHO et al., 2014), banana (DONATO et al., 2008; OLIVEIRA PINTO et al., 2014), batata (STORCK et al., 2005), café (FIRMINO et al., 2012), candeia (OLIVEIRA et al., 2011), canola (CARGNELUTTI FILHO et al., 2015), feijão (CARGNELUTTI FILHO et al., 2014), girassol (LORENTZ et al., 2010; SOUSA et al., 2015), inventário florestal (DRUSZCZ et al., 2010; VIBRANS et al., 2010; AUGUSTYNCZIK et al., 2013), mandioca e trigo (PARANAÍBA et al., 2009b), maracujá (PEIXOTO et al., 2011), milho (STORCK et al., 2010), milheto (BURIN et al., 2015), nabo (CARGNELUTTI FILHO et al., 2011), olerícolas (SANTOS et al., 2014), pimentão (LORENTZ et al., 2012), tomateiro (LÚCIO et al., 2012), tremoço (CARGNELUTTI FILHO et al., 2015), uva (MORAIS et al., 2014), mamão (SILVA et al., 2019a; 2019b), mamona (SAMPAIO FILHO et al., 2019), palma (GUIMARÃES et al., 2020).

Dentro desse contexto, é evidente que inúmeros estudos foram realizados para determinar o tamanho de parcela para diversas culturas agrícolas, fato que reforça a ideia de que para cada cultura é necessário um tamanho de parcela específico, uma vez que o tamanho de parcela varia em função da cultura estudada. Contudo, não constam na literatura estudos estatísticos sobre estimativas do tamanho e forma de parcelas experimentais para avaliação de descritores fenotípicos em palma gigante (*Opuntia ficus-indica* Mill).

Modelos de predição de colheita em palma forrageira

O fenômeno crescimento e desenvolvimento vegetal, tanto em nível de manejo como de pesquisa, requer o conhecimento das respostas das plantas ao ambiente. Neste sentido, os diversos segmentos da produção vegetal convergem na necessidade de desenvolver modelos de predição de crescimento vegetativo e de colheita com o desígnio de detectar os fatores que possam limitar o cultivo, influenciando no potencial produtivo das espécies, além de prever rendimentos em função das condições em que as plantas se desenvolvem (SOARES et al., 2014).

A análise do desempenho agronômico das espécies agrícolas é de grande interesse daqueles que se dedicam à pesquisa em produção vegetal, sendo de ordem prática e de fácil aplicação; os modelos são essenciais e eficientes para o planejamento adequado das atividades agrícolas, além de possibilitar a tomada de decisão, com vistas na redução de custos e sustentabilidade do sistema de produção. Assim, o comportamento e a expressão vegetal frente às diferentes características edafoclimáticas têm sido amplamente avaliados por meio de modelos de simulação, que incorporam simplificações dos processos de crescimento das plantas e das suas interações com o ambiente (SCARPARI et al., 2009; RAHMAN, BALA, 2010; SOARES et al., 2012; GUIMARÃES et al., 2013; SOARES et al., 2013; GUIMARÃES et al., 2014; SOARES et al., 2014).

Com o propósito de obter informações futuras e descrever o crescimento do vegetal ao longo do tempo, esses modelos, em conjunto com os dados mensurados em campo, permitem maximizar o entendimento da interação específica da cultura com o meio ambiente. Dessa forma, esse instrumento preditivo tem ampla aceitação no universo da pesquisa e das práticas agronômicas, pois possibilita entender a resposta das plantas a diferentes condições ambientais e, posteriormente, estimar a produtividade das culturas, como afirma Carvalho (2014).

Os modelos de predição podem ser ajustados para diversas finalidades da cadeia agronômica, alguns estudos contemplam a definição das melhores épocas de plantios sob sistema irrigado e condição de sequeiro (SOLER et al., 2007), fertirrigação (RINALDI et al., 2007) e previsão de colheita (SOARES et al., 2014). O conhecimento prévio dessas informações favorece o planejamento das atividades agronômicas, minimizam os custos de produção e auxiliam na comercialização dos produtos agrícolas (OGUNSUA et al., 2019)

Contudo, a elaboração de modelos de predição para a palma forrageira ainda é escassa e de baixa expressão no universo agronômico. Ainda que apresente trabalhos relacionando caracteres de componentes da produção em diferentes palmas forrageiras, a literatura carece de informações que permitam uma estimativa de produção de cladódios a partir de alguns atributos medidos na fase da pré-colheita do primeiro e segundo artículo.

Carvalho (2014) pesquisou sobre o modelo original da Zona Agroecológica - ZAE da FAO na estimativa da produtividade espacial da palma forrageira no Estado da Bahia. Segundo a pesquisadora, o território baiano apresenta oscilação do potencial produtivo da cultura por regiões, sendo que os municípios situados no Centro e Centro Sul do Estado proporcionam as maiores eficiências produtivas em decorrência da melhor disponibilidade hídrica e condição térmica mais apropriada. Todavia, quando utilizou o mesmo modelo, ZAE FAO, para a predição da colheita com base nos caracteres morfofisiológicos da planta, constatou baixo desempenho na simulação da produtividade da palma forrageira.

A associação entre características agronômicas em palma forrageira é de fundamental importância para estimar a produção de cladódios, podendo ser avaliada por meio das correlações fenotípicas, genéticas e ambientais. Assim, as correlações entre os caracteres vegetativos possibilitam ao produtor predizer a produção de matéria seca de uma determinada área cultivada com palma a partir de outros atributos da planta. Apesar disso, o sucesso da aplicação dos modelos depende substancialmente das condições locais onde o experimento foi conduzido e, por conseguinte, da qualidade dos dados usados em tais procedimentos de calibração (GUIMARÃES et al., 2013).

Por fim, a estimativa da produtividade de palma forrageira é de suma importância para o planejamento rural dos pequenos e médios produtores, sobretudo em condições de adversidades climáticas como o semiárido do nordeste brasileiro.

OBJETIVO GERAL

Objetivou-se com este estudo desenvolver modelos para a predição de colheita e estimar o tamanho ótimo de parcelas experimentais para avaliação dos descritores fenotípicos em palma forrageira 'Gigante'.

OBJETIVOS ESPECÍFICOS

Ajustar modelos por Redes Neurais Artificiais para predição de produtividade em palma forrageira e determinar os caracteres morfológicos mais importantes neste estudo.

Estimar a produtividade da palma forrageira cv. Gigante por meio de interface da análise de regressão simples e múltipla.

Comparar modelos de regressão linear simples e múltiplas e redes neurais artificiais para permitir a máxima segurança na previsão de colheita da palma forrageira 'Gigante'.

Determinar, por meio do método Hatheway (1961), tamanhos de parcelas convenientes para otimização de experimentos, visando à maior precisão, à adequação espacial e ao uso eficiente da área experimental.

Afeurir o tamanho ideal de parcelas para experimentos com a palma forrageira 'Gigante'usando o método de comparação de variâncias.

Quantificar o tamanho ótimo de parcela para palma forrageira 'Gigante' por meio do modelo de regressão com resposta linear a platô.

Determinar graficamente o formato de parcela que fornece a máxima precisão em testes de campo usando o método de informação relativa.

Comparar métodos para estimar tamanhos de parcela para avaliação das características fenotípicas em palma forrageira ‘Gigante’.

Construir um modelo *in vivo*, como ferramenta didática, com a espécie *Opuntia brasiliensis* (Willd) Haw. para representação agronômica do tamanho ótimo de parcela experimental da palma forrageira ‘Gigante’.

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CAPÍTULO I

PREDICTION OF ‘GIGANTE’ CACTUS PEAR YIELD BY MORPHOLOGICAL CHARACTERS AND ARTIFICIAL NEURAL NETWORKS

(Artigo publicado pela Revista Brasileira de Engenharia Agrícola e Ambiental)

ARTIGO 1

Prediction of 'Gigante' Cactus Pear Yield by Morphological Characters and Artificial Neural Networks[1]

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Abstract: Estimating cactus pear yield is important for the planning of small and medium rural producers, especially in environments with adverse climatic conditions, such as the Brazilian semiarid region. The objective of this study was to evaluate the potential of artificial neural networks (ANN) for predicting yield of 'Gigante' cactus pear, and determine the most important morphological characters for this prediction. The experiment was conducted in the Instituto Federal Baiano, Guanambi campus, Bahia, Brazil, in 2009 to 2011. The area used is located at 14°13'30"S and 42°46'53"W, and its altitude is 525 m. Six vegetative agronomic characters were evaluated in 500 plants in the third production cycle. The data were subjected to ANN analysis using the R software. Ten network architectures were trained 100 times to select the one with the lowest mean square error for the validation data. The networks with five neurons in the middle layer had the best results. Neural networks with coefficient of determination (R^2) of 0.87 were adjusted for sample validation, assuring the generalization potential of the model. The morphological characters with the highest relative contribution to yield estimate were total

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cladode area, plant height, cladode thickness and cladode length, but all characters were important for predicting the cactus pear yield. Therefore, predicting the production of cactus pear with high precision using ANN and morphological characters is possible.

Keywords: yield estimation, artificial logic, production, *Opuntia ficus-indica*

Predição da produtividade de palma forrageira 'Gigante' por caracteres morfológicos e redes neurais artificiais

Resumo: A estimativa da produtividade em palma forrageira é fundamental ao planejamento rural dos pequenos e médios produtores, sobretudo, em condições de adversidades climáticas como no Semiárido Brasileiro. Objetivou-se avaliar o potencial de Redes Neurais Artificiais (RNAs) na predição da produtividade em palma forrageira e determinar os caracteres morfológicos mais importantes neste estudo. O experimento foi conduzido no Instituto Federal Baiano, *Campus* Guanambi, Bahia, Brasil, no período agrícola de 2009 a 2011. A região localiza-se nas seguintes coordenadas geográficas: latitude 14° 13' 30" Sul, longitude de 42° 46' 53" Oeste de Greenwich, altitude de 525 m. Avaliou-se, em 500 plantas, seis caracteres agronômicos de natureza vegetativa no terceiro ciclo de produção. Os dados foram submetidos à análise no software R por RNAs. Dez arquiteturas de rede foram treinadas por 100 vezes, selecionando-se, ao final do treinamento, aquela com menor erro quadrático médio para os dados de validação. As redes com cinco neurônios na camada intermediária possibilitaram a máxima qualidade preditiva. Foram ajustadas redes neurais com coeficiente de determinação (R^2) de 87,21% para a amostra de validação, assegurando o potencial de generalização do modelo. Os caracteres morfológicos de maior contribuição relativa foram a área total do cladódio, altura da planta, espessura do cladódio e comprimento do cladódio; porém, todos são

importantes na predição da produtividade. Logo, é possível predizer a produção de palma forrageira com alta precisão por meio de RNAs e caracteres morfológicos.

Palavras-chave: estimativa, lógica artificial, produção, *Opuntia ficus-indica*

INTRODUCTION

Estimating cactus pear (*Opuntia ficus-indica* Mill.) production is important for the planning of small and medium producers, especially in environments with adverse climatic conditions, such as the Brazilian semiarid region (BSA). This plant is an energetic source in the nutrition of ruminants (AGUIAR et al., 2015a; AGUIAR et al., 2015b). However, this crop needs technological tools to increase yield since it can minimize risks of maintaining cattle herds in the dry season.

The development of prediction models for this forage crop is scarce and inexpressive in agronomic studies. Studies report components of the production in different species of forage *Opuntia*, but they lack information on estimating cladode production from plant attributes, especially those measured in the pre-harvest phase of the first and second cladode (Padilha Junior et al., 2016).

Artificial neural networks (ANN) is a successful tool to describe, substantiate, and elucidate high-complexity issues in the field of modeling (Jana et al., 2012; Jana & Mohanty, 2012; Brasileiro et al., 2015; Soares et al., 2015; Azevedo et al., 2015, 2017; Aquino et al., 2016a, 2016b). Thus, the use of ANN in agronomic modeling for the cactus pear crop can be efficient for predicting yield.

ANN has better performance compared to other statistical modeling techniques since it has universal fit of functions (Gianola et al., 2011), is non-parametric, admits data loss, and does not require much prior information about the phenomena to be modeled (Azevedo et al., 2015).

Thus, objective of this study was to evaluate the potential of artificial neural networks for predicting yield of 'Gigante' cactus pear, and determine the most important morphological characters for this prediction.

MATERIAL AND METHODS

The experiment was conducted in the Federal Institute for Education, Science, and Technology of Bahia, Guanambi campus, Brazil, from 2009 to 2011. The area used is located at 14°13'30 S and 42°46'53"W, and its altitude is 525 m. The soil of the area was classified as Entisol, and the region has annual average precipitation of 680 mm and annual average temperature of 26 °C (CODEVASF, 2007).

The evaluations were carried out in a uniformity test with the 'Gigante' cactus pear, at 930 days after planting (DAP), in the third production cycle. A blank test was conducted with spacing of 2.0 x 0.2 m, using a planting template, with 25,000 plants ha^{-1}. The soil were prepared with subsoiling, plowing and harrowing at 35, 25 and 20 cm depths, respectively. An organic fertilizer consisting of aged sheep manure was applied at a rate of 40 L m^{-1}. The planting was arranged in 12 rows with 550 plants each, considering the 50 central plants of the ten central rows for evaluation, totaling 500 plants and an area of 200 m^2. This test does not have treatments and the crop practices were homogeneous in the whole area (Storck et al., 2011), thus constituting a blank or uniformity test.

The vegetative characters evaluated were: cladode length (CL; cm), cladode width (CW; cm), cladode thickness (CT; mm), number of cladodes (NOC), plant height (PH; cm), cladode biomass (CB; Mg ha^{-1} $year^{-1}$), cladode area (CA = CL x CW x 0.693, cm^2), and total cladode area (TCA = ((AC x NR q) / 10,000) x 2; m^2) in the third production cycle.

The data were evaluated on R (R Development Core Team, 2012) using artificial neural networks (ANN). Both the input (CL, CW, CT, NOC, TCA and PH) and output data (PROD) were normalized into a 0 to 1 interval by the normalize data function of the package RSNNS to increase the efficiency in network training (Bergmeir & Benítez, 2012).

In the ANN analysis, 80% of the data (information of 400 plants) were intended for training the network, and 20% for the validation analysis (information of 100 plants). The samples from the training and validation plants were randomly chosen. The multilayer perceptron (MLP) neural model was used. The MLP function of the RSNNS package, with backpropagation algorithm and learning rate of 0.1, was applied to improve the MLP networks.

The maximum number of training was 500 and the activation functions for the intermediate and output layers fitted logistic and linear models, respectively. Ten architectures were tested, with 1, 2, 3, ..., 9 and 10 neurons in the middle layer to define the best network structure. The free parameters is generated randomly at the beginning of training and these initial values can influence the result of the training (Soares et al., 2014), thus, each ANN architecture was trained 100 times. The network that provided the best fit was selected considering the means of the mean square error (MSE) for the validation sample.

The best network architecture selected were subjected to 1,000 new trainings. The strategy of selecting the best network architecture and carry out several trainings for this configuration aims to reduce computational effort by avoiding performing training for each architecture. In addition, the relative importance of the input characteristics was obtained using Garson' method (Garson, 1991) by the Garson function (Neural Net Tools package).

The predictive capacity in the training of the networks was tested using a regression analysis on the predicted yield found with the selected network for the sample validation. The intercession point was fixed at the origin of the Cartesian plane for a practical interpretation of the regression model. The t test was used for the angular coefficient of the line to verify if it is equal to or different from 1. Thus, the efficiency in the prediction process is based on the value 1 for the line coefficient and the high coefficient of determination of the model.

RESULTS AND DISCUSSION

A high variation was found for the yield per plant, with estimates of 0.60 to 34.70 kg plant^{-1} of fresh biomass, and coefficient of variation of 52.24% (Table 1). Regarding the morphological data, the highest coefficients of variation were found for the number of cladodes (NOC) (37.08) and total cladode area (TCA) (41.24%). The cladode length and width had the greatest morphological uniformity, with coefficients of variation of 7.07 and 8.39%, respectively. However, cladode thickness (CT) showed high phenotypic variability (Table 1). According to Azevedo et al. (2015), the high variability of morphological characters is essential for the generalization in the ANN. Thus, trained ANN can also be used in other prediction models, similar to those in the present study.

Table 1. Descriptive analysis of the cactus pear cladode length (CL), width (CW), thickness (CT), number (NOC), plant height (PH), total area (TCA) and fresh biomass yield (YIELD)

Parameters	CL (cm)	CW (cm)	CT (mm)	NOC (un)	PH (m)	TCA (m²)	YIELD (kg plant^{-1})
Minimum	19.56	10.11	4.87	3	0.46	0.13	0.60
Average	29.74	14.54	13.56	20.88	1.18	1.29	12.27
Maximum	36.35	19.44	24.65	48	1.89	2.94	34.70
Std. Deviation	2.10	1.22	4.29	7.74	0.22	0.53	6.41
Coefficient of variation (%)	7.07	8.39	31.61	37.08	18.86	41.24	52.24
Pearson's correlation							
CL (cm)	1	0.74**	0.07^{ns}	0.19**	0.49**	0.44**	0.39**
CW (cm)	0.74**	1	0.21**	0.16**	0.45**	0.43**	0.39**
Erq (mm)	0.07^{ns}	0.21**	1	0.08^{ns}	-0.13**	0.12**	0.26**
NOC (und)	0.19**	0.16**	0.08^{ns}	1	0.56**	0.94**	0.81**
PH (m)	0.49**	0.45**	-0.13**	0.56**	1	0.64**	0.56**
TCA (m²)	0.44**	0.43**	0.12**	0.94**	0.64**	1	0.86**
Yield (kg plant^{-1})	0.39**	0.39**	0.26**	0.81**	0.56**	0.86**	1

^{ns}Non-significant ($p > 0.05$); *Significant ($0.01 < p \leq 0.05$); **Significant ($p \leq 0.01$)

Ten network architectures were evaluated for the ANN. A significant number of training sessions was performed, which showed the adjustment of the network with two neurons in the middle layer presenting the largest mean square errors (MSE) (Figure 1A) and the lowest coefficient of determination (R^2). Soares et al. (2014) point out the importance of intensive network training in the search for the most appropriate architecture.

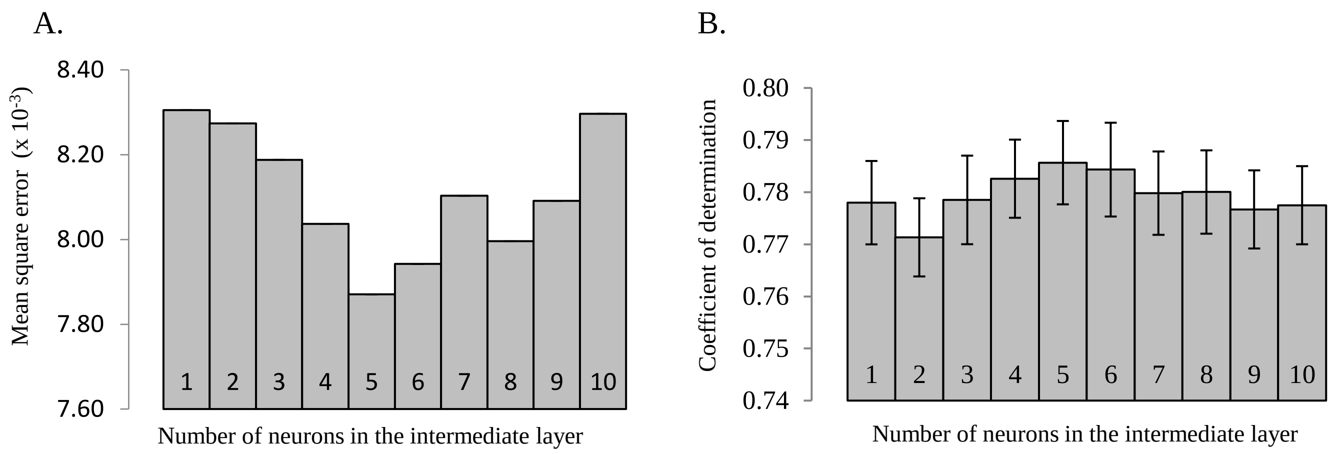

Figure 1. Estimates of mean square error (A) and coefficient of determination (B) considering different numbers of neurons in the intermediate layer

The smallest mean square error (MSEs) was obtained when five neurons were tested in the intermediate layer (Figure 1A). The smaller the MSEs, the greater the proximity of the predicted MSE by ANN to the real values; thus, a low MSE indicates a high efficiency of the networks. Regarding the coefficient of determination (R^2), satisfactory results were obtained for the average of five neurons in the intermediate layer, with fitting of the data of 78.57% (Figure 1B). The deviations presented represent the lower and upper limits from the 95% confidence level obtained by bootstrap with 10,000 simulations.

The determination of the optimal number of neurons in the intermediate layer is important. According to Soares et al. (2015), the best relationship between the number of training samples and the number of intermediate connections must be considered in the selection of the prediction model; the latter should be higher than 2 to reach the least average relative error of validation. Similar prediction studies confirm that the addition of neurons per layer does not always favor the performance of the model (Soares et al., 2014; Azevedo et al., 2015, Aquino et al., 2016a). According to Silva et al. (2010), the continuous addition of neurons in the network in the training phase allows memorizing studied data, but does not identify the probable associations between the data inserted in the input and output layers—a technical condition called overfitting. The network structure with five neurons in the middle layer is shown in Figure 2A.

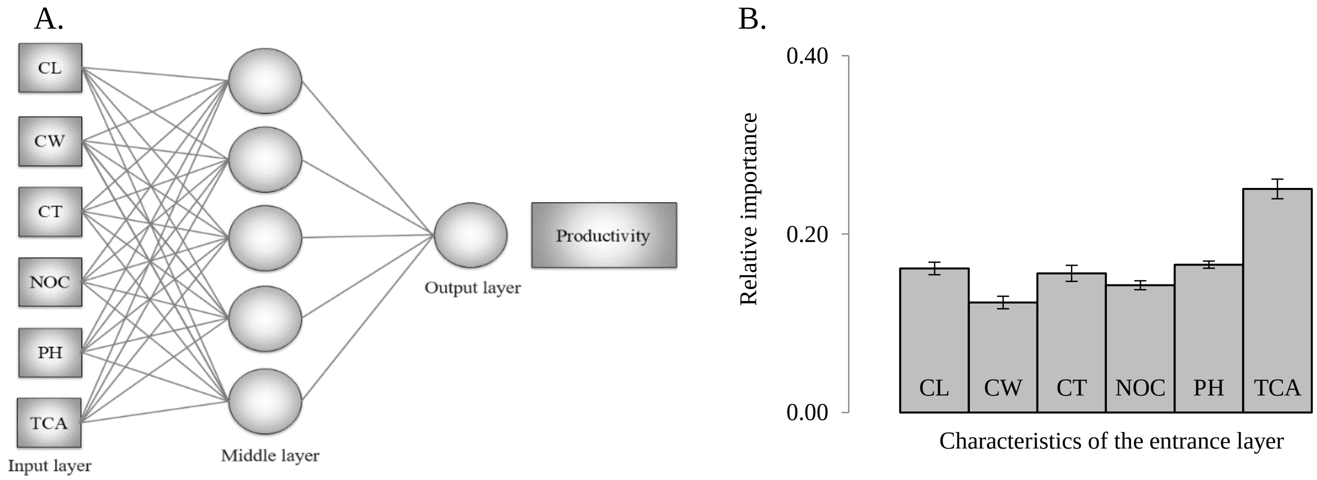

Figure 2. Topology of the best adjusted network (A) and relative contribution to yield (B), obtained by Garson's method (Garson, 1991), of the agronomic parameters cladode length (CL), cladode width (CW), cladode thickness (CT), number of cladode (NOC), plant height (PH), and total cladode area (TCA), presented in the input layer for the prediction of cactus pear yield by artificial neural networks

According to the relative importance of the responses obtained by Garson’s method (Garson, 1991), the total cladode area (TCA) was the most important (Figure 2B), with a relative contribution to yield of 25.07%. The highest expression of the TCA correlates with the highest coefficient of correlation with yield, 0.86 (Table 1). Cladode width (CW) had the lowest relative contribution to yield (12.33%).

Neural networks with R^2 of 0.87 were fitted for the validation sample (Figure 3A). The high value of R^2, and the non-significance of the angular coefficient of the line (Ho: b = 1), proves the prediction efficiency and generalization of the model. Gianola et al. (2011) stated that good results obtained by artificial neural networks could be explained by the adequate adjustment to the nonlinear systems. Moreover, according to Aquino et al. (2016a), ANN consider numerous explanatory variables concomitantly in the model that does not always present good results by other statistical models, such as multiple linear regression. Several researchers also confirmed the efficiency of artificial intelligence found in this study (Azevedo et al., 2015; Brasileiro et al., 2015; Soares et al., 2015; Aquino et al., 2016a, 2016b).

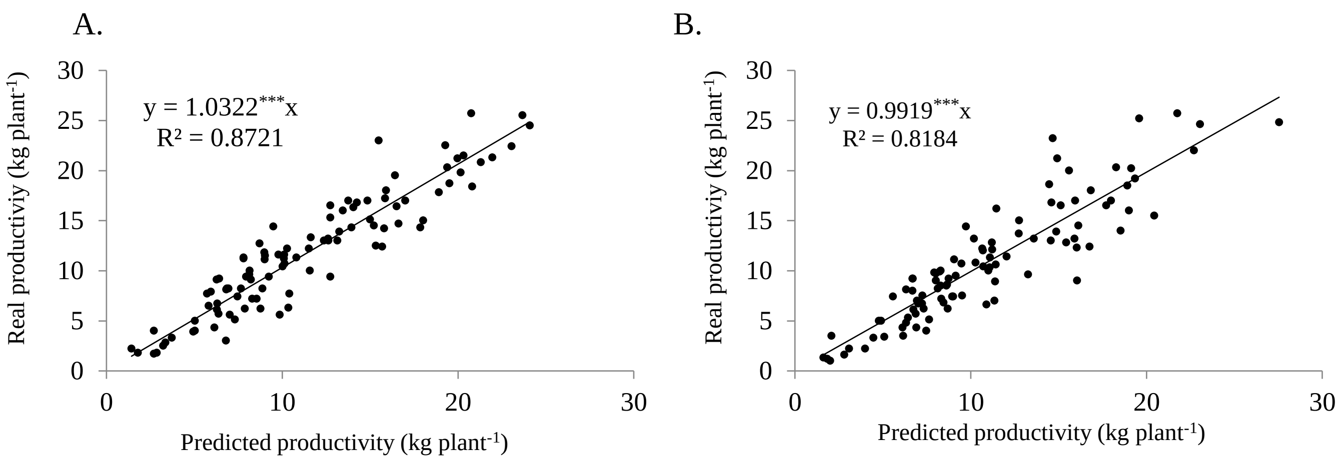

Figure 3. Graphical representation of the quality of artificial neural networks in predicting cactus pear yield for the validation sample considering vegetative characters (A) and excluding characteristic of lower relative contribution to yield (B). ***significant ($p \leq 0.001$), by the t test.

The efficiency of using of MLP type ANN to obtain agronomic estimates was confirmed by some researchers (BINOTI et al., 2013; MIGUEL et al., 2016). According to Vendruscolo et al. (2017), ANN models present statistical indicators with errors of estimation lower than 10%, thus ensuring the prediction of the phenomena.

New ANN's were adjusted excluding the characteristic of lower relative contribution to yield in this study (CW) obtaining a coefficient of determination of 0.82 (Figure 3B). This lower estimate, when compared to the adjusted networks with all the characteristics (Figure 2B), indicates that its exclusion for yield prediction is not feasible, even though the CW had a smaller contribution to yield.

Therefore, cactus pear yield can be estimated by agronomic characteristics measured in the field (CL, CW, CT, NOC, PH, and TCA). The results found in this study show that the application of the ANN models allows predicting cactus pear yield, and is an efficient and strategic tool in the decision making of its production, especially for agricultural planning for periods of scarcity or low feed availability for animal nutrition.

CONCLUSIONS

1 - Predictions of forage cactus pear yield are obtained with high efficiency through multi-layer perceptron-type artificial neural networks.

2- The morphological characters with the greatest relative contribution to predicting forage cactus pear yield are total cladode area, plant height, cladode thickness and cladode length.

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CAPÍTULO II

REGRESSION MODELS FOR YIELD PREDICTION IN CACTUS PEAR CV. GIGANTE

(Artigo aceito pela Revista Brasileira de Engenharia Agrícola e Ambiental)

ARTIGO 2

Regression models for yield prediction in cactus pear cv. Gigante[2]

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ABSTRACT: The understanding of plant behavior and its reflexes on yield is essential to rural planning; thus, the biomathematical models are promising in the yield prediction of cactus pear cv. Gigante. This study aimed to adjust, through simple and multiple regression analysis, models for predicting the yield of cactus pear cv. Gigante. The study, using homogeneous treatments, was developed at the Instituto Federal Baiano, Campus of Guanambi, Bahia, Brazil. Data were collected in an area consisting of 384 basic units (plants), in which the yield, defined as a dependent variable, and the predictor variables: plant height (PH), cladode length (CL), cladode width (CW), and cladode thickness (CT), number of cladodes (NC), cladode area (CA), and total cladode area (TCA) were evaluated. Simple linear regression models, multiple regression models only with simple effects for the explanatory variables, and the multiple regression models considering the simple and quadratic effects, and all its possible interactions were adjusted. From this last model, a reduced model was obtained by discarding the less relevant effects, using the Stepwise methodology. The use of the vegetative traits, TCA, NC, CA, CL, CT, and CW, through the adoption of multiple linear regression, quadratic interaction

[2] Artigo aceito pela Revista Brasileira de Engenharia Agrícola e Ambiental

or just the variable TCA by the use of simple linear regression, allows the yield prediction of cactus pear, with adjusted R^2 of 0.82, 0.76, and 0.74, respectively.

Keywords: *Opuntia* sp., modeling, prediction, yield

Modelos de regressão para predição de produtividade em palma forrageira cv. Gigante

RESUMO: O entendimento sobre o comportamento vegetal e seus reflexos sobre a produtividade é essencial ao planejamento rural, com isso, os modelos biomatemáticos são promissores na predição da produtividade da palma forrageira cv. Gigante. Objetivou-se com este estudo ajustar por meio de análises de regressão simples e múltipla modelos para predição da produtividade da palma forrageira cv. Gigante. O estudo, em formato de homogeneidade de tratamentos, foi desenvolvido no Instituto Federal Baiano, Campus Guanambi, Bahia, Brasil Os dados foram coletados em área constituída de 384 unidades básicas, nas quais se mensuraram a produtividade, definida como variável dependente, e as variáveis preditoras: altura da planta (PH), comprimento (CL), largura (CW) e espessura do cladódio (CT), número de cladódio (NC), área do cladódio (CA), e área total do cladódio (TCA). Foram ajustados modelos de regressão linear simples, modelos de regressão múltipla com efeitos simples apenas para as variáveis explicativas e modelos de regressão múltipla, considerando tanto os efeitos simples, quadráticos e todas as suas interações possíveis. A partir deste último modelo citado, foi obtido um modelo reduzido pelo descarte dos efeitos menos relevantes, por meio da metodologia Stepwise. O uso das características vegetativas TCA, NC, CA, CL, CT e CW, por meio de adoção da regressão linear múltipla, interação quadrática ou somente a variável TCA pelo emprego da regressão linear simples, permite a predição da produtividade da palma forrageira, com R^2 ajustado de 0,82, 0,76 e 0,74, respectivamente.

Palavras-chave: *Opuntia* sp, modelagem, predição, produtividade

INTRODUCTION

The cactus pear cv. Gigante (*Opuntia fícus-indica* Mill.) presents excellent forms of adaptations to the semiarid ecosystem, mainly due to the photosynthetic process CAM (Crassulacean Acid Metabolism) characterized by stomatal opening and CO2 capture at night (Taiz et al., 2017), and with efficient mechanisms of the water use (Silva et al., 2015).

Due to the high nutritional, energy, and water value, this forage stands out as a strategic food source in the nutrition of ruminants. Likewise, besides the potential to meet the needs of the herd, in balanced diets, the species assumes singular importance in the period of food scarcity and water restriction (Marques et al., 2017).

However, the success of agricultural activity goes beyond production. In this context, proper planning is essential because it allows the producer a tool to estimate production by non-destructive morphometric measures (Guimarães et al., 2013; 2018; 2019). Thus, organize a technical reserve to ensure the raw material supply to the animals continuously and safely, especially in advance of the dry season.

In the search for understanding about which vegetative descriptors are most associated with the production, as well as the possibility of using these to predict yield (Guimarães et al., 2014), aiming at defining the number of animals to be fed or biomass volume to be commercialized, the use of simple linear regression (SLR) (Bertolin et al., 2017), multiple linear regression (MLR) (Soares et al., 2014; Mantai et al., 2015) and the polynomial and quadratic regression models (Amaral et al., 2017) have been used as a reliable tool.

Given the above, the analysis of plant behavior and its reflexes on productivity is essential to rural planning. Thus, biomathematical models are promising in the prediction of crop yield. Therefore, this study aimed to adjust, through simple and multiple regression analysis, models for predicting the yield of cactus pear cv. Gigante.

MATERIAL AND METHODS

The study was carried out at Instituto Federal Baiano, Campus of Guanambi, Bahia, Brazil, between 2009 and 2011, at geographical coordinates, 14°13'30" S, 42°46'53" W and altitude of 525 m. The soil was classified as *Entisols Lithic*. The average annual precipitation and temperature are 670.2 mm and 25.9 °C, respectively (CODEVASF, 2018).

The study followed the format of treatment homogeneity or uniformity trial, in which the entire area implanted with the cactus pear cv. Gigante was submitted to the same agronomic conditions and evaluated at 930 days after planting (DAP) in the third production cycle.

The useful planting area was composed of eight central rows, with 48 plants per row, making 384 basic units (plants). The fresh mass yield of the cladodes (Prod, t ha^{-1}), considered the response variable, was determined in the third production cycle. Also, the following predictor variables were evaluated, plant height (PH, cm); cladode length (CL, cm); cladode width (CW, cm), measured using a graduated measuring tape; cladode thickness (CT, mm), defined by the caliper measuring in the central part of the cladode; the number of cladodes (NC, nº), direct count; cladode area (CA, cm^2), and total cladode area (TCA, m^2), which were estimated by Equations. 1 and 2, respectively, according to models adopted by Donato et al. (2017) and Padilha Junior et al. (2016).

$$CA = CL \times CW \times 0.693 \tag{1}$$

$$TCA = ((CA \times NC)/10{,}000) \times 2 \tag{2}$$

where:

CA – cladode area, cm^2;

CL – cladode length, cm;

CW – cladode width, cm;

TCA – total cladode area, m^2; and,

NC – number of cladodes.

Through Pearson's correlation, associations between the morphological variables analyzed were evaluated. In the sequence, the simple linear regression models (Equations 3 and 4), the multiple regression models only with main effects for the explanatory variables (Equations 5 and 6), and the multiple regression models considering simple and quadratic effects and all its possible interactions (Equation 7) were adjusted by the methods of least squares.

$$Prod_i = \beta_0 + \beta_1 TCA_i + e_i \quad (3)$$

$$Prod_i = \beta_0 + \beta_1 NC_i + e_i \quad (4)$$

$$Prod_i = \beta_0 + \beta_1 PH_i + \beta_2 TCA_i + \beta_3 NC_i + \beta_4 CA_i + \beta_5 CL_i + \beta_6 CT_i + \beta_7 CW_i + e_i \quad (5)$$

$$Prod_i = \beta_0 + \beta_1 TCA_i + \beta_2 CA_i + \beta_3 CL_i + \beta_4 CT_i + \beta_5 CW_i + e_i \quad (6)$$

$$Prod_i = \beta_0 + \beta_1 CW_i + \beta_2 CT_i + \beta_3 TCA_i + \beta_4 CW_i^2 - \beta_5 CT_i^2 + \beta_6 TCA_i^2 + \beta_7 CL_i CT_i + \beta_8 CW_i TCA_i + \beta_9 CW_i TCA_i^2 + \beta_{10} PH_i NC_i + \beta_{11} PH_i CL_i^2 + \beta_{12} PH_i CT_i^2 + \beta_{13} PH_i NC_i^2 + \beta_{14} NC_i PH_i^2 + \beta_{15} TCA_i CW_i^2 + \beta_{16} TCA_i PH_i^2 + \beta_{17} CW_i^2 CT_i^2 + \beta_{18} CW_i^2 TCA_i^2 + \beta_{19} CT_i^2 PH_i^2 + \beta_{20} CT_i^2 TCA_i^2 + \beta_{21} PH_i^2 NC_i^2 + \beta_{22} PH_i^2 TCA_i^2 + e_i) \quad (7)$$

where:

$Prod_i$ – Yield of green mass of cladodes associated with i^{th} observation, t ha^{-1};

PH – plant height, cm;

TCA – total cladode area, m^2;

NC – number of cladodes, nº;

CA – cladode area, cm^2;

CL – cladode length, cm;

CT – cladode thickness, cm;

CW – cladode width, cm;

β_0 – intercept;

$\beta_{1....n}$ – regression coefficients of the models; and,

e_i – the error associated with the i^{th} observation.

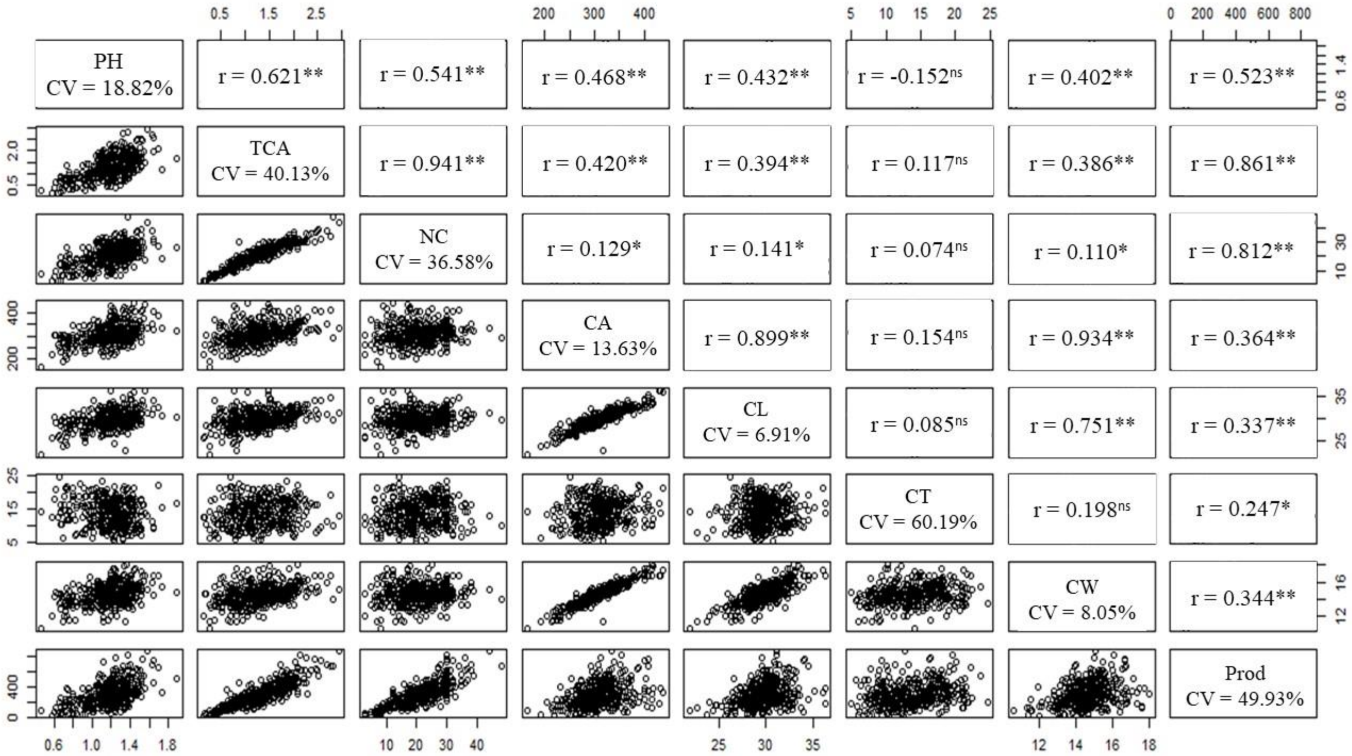
The determination coefficient (R^2), the adjusted determination coefficient (R^2_{aj}), the Akaike Information Criterion (AIC) (Akaike, 1974), the Bayesian Information Criterion (BIC), and the selection criterion defined by the loglikelihood, which represents the logarithm value of the likelihood function considering the parameter estimates were considered for the selection of regression models.

Based on the model represented by the equation (Eq. 7), the Stepwise methodology was used to discard the less relevant variables. Regression analyzes were performed using the R software with the aid of the lm and step functions.

The regression analysis of the estimated productivity was performed with the observed values to test the predictive ability of the regression models. Subsequently, the point of intersection at the origin of the Cartesian plane was fixed, and the significance of the slope of the line was tested by the t-test, assuming as a null and alternative hypothesis the possibility of this coefficient being equal to or different from 1, respectively. Thus, if the coefficient of determination is high and the slope of the line does not differ from 1, the efficiency of prediction is assumed. The data were analyzed using the R software (R Development Core Team, 2016).

RESULTS AND DISCUSSION

The coefficients of variation and correlation values of vegetative traits with the yield of cactus pear cv. Gigante, as well as their significance, are shown in Figure 1. About the variability of generic traits, Gomes (2000) proposed stratifying the coefficient of variation (CV) at four categorical levels. Thus, when the range of variation is included in the classes of <10; 10.01 - 20; 20.01 - 30, and >30%, the variability is considered low, medium, high, and very high, respectively.



PH - Plant height; TCA - Total cladode area; NC - Number of cladodes; CA - Cladode area; CL - Cladode length; CT - Cladode thickness; CW - Cladode width; Prod - Yield of cactus pear cv. Gigante; ^{ns} - Not significant ($p > 0.05$); * - Significant ($0.01 < p \leq 0.05$); ** - Significant ($p \leq 0,01$).

Figure 1. Scatter plots, coefficients of variation, and the estimated correlation between vegetative traits.

The CVs of the evaluated descriptors ranged between 6.91 and 60.19%, with the lowest values in the traits associated with the cladode, such as the area, length, and width of the cladode, except for the cladode thickness which showed very high variability (Gomes, 2000). Donato et al. (2017) report that the dimensions of the cladodes, especially the length and width, are determined by genotypic factors, with the low influence of the environment. However, the proper management of the crop favors the cladode thickness and, consequently, the increase in yield.

On the other hand, several studies report the wide variability of cladode thickness, as this descriptor varies over its length, although usually the thickest or central region of the cladode is measured. Also, the cladode thickness, as it is linked to photosynthetic capacity and water storage (Scalisi et al., 2016), is greatly influenced by the growth and vegetative development stage of the crop (Silva et al., 2010; Pinheiro et al., 2014; Silva et al., 2015).

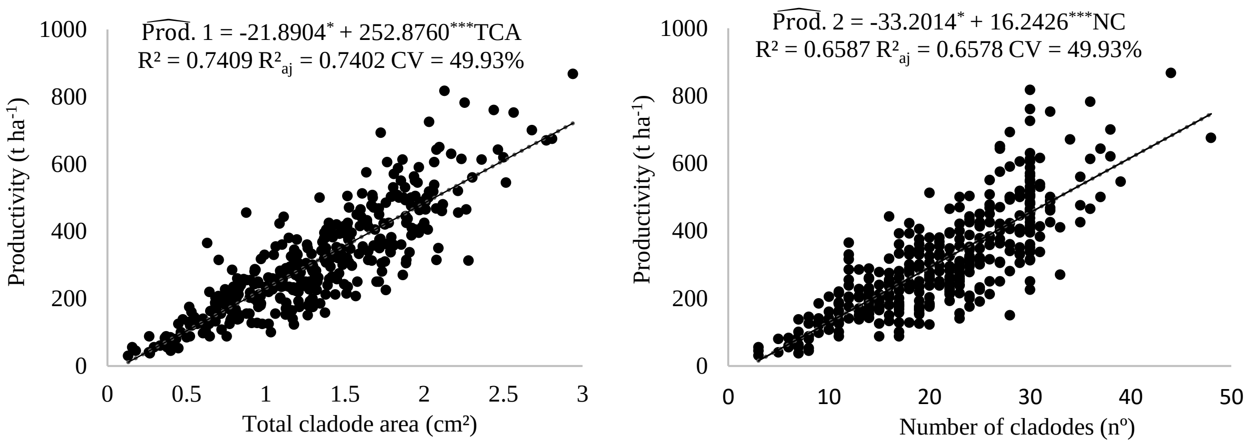
The evaluated descriptors have a positive linear association with each other, which denotes, besides the high degree of relationship of vegetative variables with the yield, considerable potential of these variables to compose the prediction model.

Similarities between these results are found in Pinheiro et al. (2014) with cactus pear for all evaluated clones. Since, in this referenced study, the number of cladodes of the cactus pear expressed a high correlation with the structural traits such as the plant height and width, with significant effects on the crop yield.

It is observed that the highest values of the correlation coefficient were associated with the traits, total cladode area, number of cladodes, and plant height, followed by variables directly related to the cladode, such as the area, length, width, and thickness (Figure 1). These results are similar to other studies on phenotypic correlation, in which, usually, the variables total cladode area and the number of cladodes express a strong relationship with the variability of cladode yield (Silva et al., 2010; 2014; Pinheiro et al., 2014; Padilha Junior et al., 2016).

By the simple linear regression procedure, compact functions were adjusted to estimate yield in cactus pear cv. Gigante, with the significance of the regression coefficients and similarity between R^2 and adjusted R^2 (Figures 2A and B).

A. B.



*, *** - Significant at $0.01 < p \leq 0.05$ and at $p \leq 0.001$ by t test, respectively.

Figure 2. Estimation of productivity and the quality of adjustment by the predictive variable total cladode area (A) and the number of cladodes (B) of cactus pear cv. Gigante.

Predictive models allow estimating yield practically and objectively in the field since it only includes an explanatory variable that is easy to determine. However, besides the best adjustment of R^2, the equation $\widehat{Prod}$. 1 has a higher predictive quality by the AIC information criterion when compared to the model $\widehat{Prod}$. 2.

Models composed of variables that are easy to measure in the field are studied because they ensure practical applicability, favoring the use of the predictive tool with the insertion of values of a variable of direct measurement in the field, mainly as observed for the model of simple linear regression using the variable, number of cladodes (Figure 2). In this context, Guimarães et al. (2013) adjusted models with components of the simple determination to estimate banana yield only by directly counting the number of hands in the bunch.

By regression analysis with the multiple linear function, models were tested to determine the yield of cactus pear cv. Gigante, according to the results presented in Table 1. The t-test for the regression models was highly significant ($p \leq 0.001$).

Table 1. Parameters of the multiple linear regression analysis of the yield (Prod) according to the traits: PH: plant height; TCA: total cladode area; NC: number of cladodes; CA: cladode area; CL: cladode length; CT: cladode thickness; CW: cladode width.

Models	Adjustment quality assessors			R^2	R^2_{aj}
	AIC	BIC	loglikelihood		
$Prod_i\,3 = \beta_0 + \beta_1 PH_i + \beta_2 TCA_i + \beta_3 NC_i + \beta_4 CA_i + \beta_5 CL_i + \beta_6 CT_i + \beta_7 CW_i + e_i$	4420.73	4456.28	-2201.36	0.7644	0.7600
$Prod_i 4 = \beta_0 + \beta_1 PH_i + \beta_2 TCA_i + \beta_3 CA_i + \beta_4 CL_i + \beta_5 CT_i + \beta_6 CW_i + e_i$	4418.79	4450.39	-2201.39	0.7644	0.7606
$Prod_i 5 = \beta_0 + \beta_1 PH_i + \beta_2 TCA_i + \beta_3 CA_i + \beta_4 CL_i + \beta_5 CT_i + e_i$	4417.10	4444.76	-2201.55	0.7642	0.7611
$Prod_i 6 = \beta_0 + \beta_1 PH_i + \beta_2 TCA_i + \beta_3 CA_i + CT_i + e_i$	4415.23	4438.93	-2201.61	0.7641	0.7616
$Prod_i 7 = \beta_0 + \beta_1 PH_i + \beta_2 TCA_i + \beta_3 CT_i + e_i$	4414.31	4434.07	-2202.16	0.7634	0.7616
$Prod_i 8 = \beta_0 + \beta_1 TCA_i + \beta_2 CT_i + e_i$	4413.71	4429.51	-2202.86	0.7626	0.7613

AIC - Akaike information criteria; BIC - Bayesian information criterion; R^2 - Coefficient of determination; R^2_{aj} - Adjusted determination coefficient.

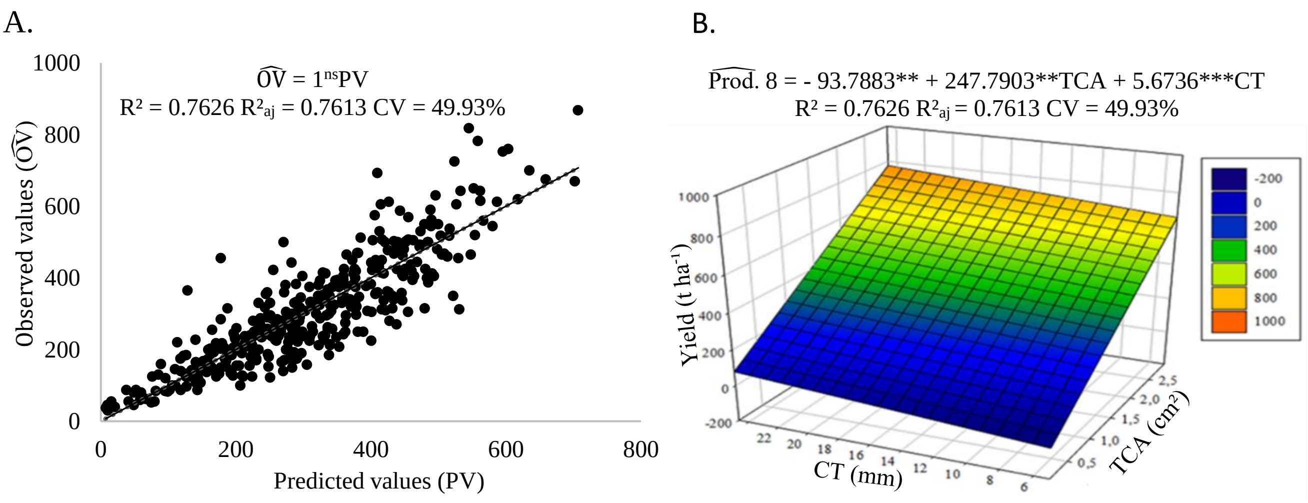
The yield of cactus pear cv. Gigante showed a significant correlation with all the traits analyzed (Figure 1), thus justifying the use of these variables as yield predictors. Besides the predictive capacity, the variables that make up the models presented have the advantage of direct measurement in the field in a non-destructive way (Guimarães et al., 2013; 2014).

The quality indicators AIC, BIC, and loglikelihood demonstrated that the model $Prod_i$ 8 has more significant potential for the prediction of cactus pear yield with R^2 of 0.7626 and R^2_{aj} = 0.7613 (Table 1).

However, for the tested models, the determination coefficient remained with the same approximate adjustment quality (Table 1), despite excluding vegetative traits with moderate and high correlation with yield (Figure 1), but with no significant effect to compose the model, such as plant height and the number of cladodes, respectively (Table 1). Similarly, Soares et al. (2014) and Leal et al. (2015) showed the stability of R^2 with the association of significant variables with the prediction model.

Based on the adjustment indexes of the models, presented in Table 1, and on the behavior of the equations that estimate yield, the multiple linear regression model allows to predict, in an acceptable way, the yield of the cactus pear through the vegetative traits, total cladode area, and cladode thickness, with simple determination in the field (Donato et al., 2017; Padilha Junior et al., 2016), which favors the practical use of the model.

The predicted values and the observed values were listed in Figure 3A, considering the value of the slope as a determinant of the model to attest to the quality of this multiple linear regression model. This procedure is justified both by the statistical bias in search of highly significant parameters and by the need to obtain a more compact and robust model. Figure 3B represents the relationship between cactus pear yield and the predictor variables, total area of cladode, and cladode thickness. The coefficients of variation shown in Figures 3A and 3B are associated with the observed yield data. In this context, Soares et al. (2015) add that the model of the easy practical application must be composed by the smallest number of variables possible, with objective determination in the field and precise answer about the inference carried out.



CV - Coefficients of variation associated with observed yield data; TCA - Total cladode area; CT - cladode thickness; ns - Not significant ($p > 0.05$); **, *** - Significant at $p \leq 0.01$ and at $p \leq 0.001$ by t test, respectively.

Figure 3. Relationship between estimated and observed values (A) and response surface of cactus pear cv. Gigante with the vegetative traits, total cladode area, and cladode thickness (B).

Still, regarding the adjustment of the regression models expressed by the coefficient of determination (R^2), there was no difference between the equations (Table 1) regarding the predictive quality to explain the behavior of the data. However, the model $\widehat{Prod.}\ 8 = -93.7883^{**} + 247.7903^{***}TCA + 5.6736^{***}CT$ as it contains only two descriptors directly related to the cladode (TCA and CT), it becomes more simplified, adequate, and practical.

As for the indexes that define the quality of the equation adjustment, AIC, BIC, and loglikelihood, the lowest estimated values were associated with the Equation 8 model, therefore, defined as the most appropriate (Table 1) as it presents the greatest proximity between the observed values and the estimated ones (Mello et al., 2018). Leal et al. (2015) argue about the importance of tools that measure the accuracy of the model to substantiate selection in practice.

The values of AIC, BIC, and loglikelihood are directly proportional to the sum of squares of errors. Therefore, the lower the value, the better the quality of the adjustment, defined by the smaller relative distance between the predicted and the real values (Leal et al., 2015).

Thus, the variables, being easy to determine in practice and in a direct non-destructive way, enable the researcher or producer to estimate, with high efficiency, the yield of the cactus pear cv. Gigante. With this, it is configured as an essential tool for the success of rural planning, above all, about the size of the herd to be fed in the drought period or dry season; in which, usually, due to lack of planning, the highest mortality rate of animals occurs in the Brazilian semiarid region, compromising the economic viability of the activity and, consequently, the permanence of man in the field (Marques et al., 2017).

Also, it is worth considering that water is a limiting factor in animal production in regions of arid and semi-arid climates, and the use of palm in the diet of ruminants in drought periods helps animals to supply most of their water requirements (Borland et al., 2014). With this, the estimate of the productivity of the cactus pear cv. Gigante is of great importance since the possibility of predicting the food volume for ruminants achieves a dual purpose with the supply of dry matter and water.

The regression models obtained to estimate the yield of cactus pear cv. Gigante considering interactions and quadratic effects are shown in Table 2. Thus, the most appropriate model was selected according to its highest precision, which is determined by the lowest AIC value, 3290.37.

Table 2. Regression model selected by the Stepwise algorithm methodology, based on the Akaike Information Criterion (AIC).

Regression models	AIC
$Prod_i\ 9 = \beta_0 + \beta_1 CL_i + \beta_2 CW_i + \beta_3 CT_i + \beta_4 PH_i + \beta_5 NC_i + \beta_6 TCA_i + \beta_7 CL_i^2 + \beta_8 CW_i^2 + \beta_9 CT_i^2 + \beta_{10} CA_i^2 + \beta_{11} NC_i^2 + \beta_{12} TCA_i^2 + \beta_{13} CL_i CW_i + \beta_{14} CL_i CT_i + \beta_{15} CL_i NC_i + \beta_{16} CL_i TCA_i + \beta_{17} CL_i CL_i + \beta_{18} CL_i CT_i^2 + \beta_{19} CL_i NC_i^2 + \beta_{20} CW_i CL_i^2 + \beta_{21} CW_i CA_i^2 + \beta_{22} CW_i NC_i^2 + \beta_{23} LC_i TCA_i^2 + \beta_{24} CT_i NC_i + \beta_{25} CT_i CL_i^2 + \beta_{26} CT_i CW_i^2 + \beta_{27} CT_i CT_i^2 + \beta_{28} CT_i CA_i^2 + \beta_{29} CT_i NC_i^2 + \beta_{30} PH_i NC_i + \beta_{31} PH_i CW_i^2 + \beta_{32} PH_i CA_i^2 + \beta_{33} NC_i TCA_i + \beta_{34} NC_i CW_i^2 + \beta_{35} NC_i CT^2{}_i + \beta_{36} NC_i CA_i^2 + \beta_{37} NC_i NC_i^2 + \beta_{38} NC_i TCA_i^2 + \beta_{39} TCA_i CL_i^2 + \beta_{40} TCA_i CW_i^2 + \beta_{41} TCA_i NC_i^2 + \beta_{42} TCA_i TCA_i^2 + \beta_{43} CL_i^2 CW_i + \beta_{44} CL_i^2 CT_i^2 + \beta_{45} CL_i^2 CA_i^2 + \beta_{46} CL_i^2 NC_i^2 + \beta_{47} CL_i^2 TCA^2{}_i + \beta_{48} CW_i^2 CT_i^2 + \beta_{49} CW_i^2 CA^2{}_i + \beta_{50} CW_i^2 NC_i^2 + \beta_{51} CW_i^2 TCA_i^2 + \beta_{52} CT_i^2 CA_i^2 + \beta_{53} CA_i^2 NC_i^2 + \beta_{54} CA_i^2 TCA_i^2 + \beta_{55} NC_i^2 TCA_i^2 + e_i$	3312.43

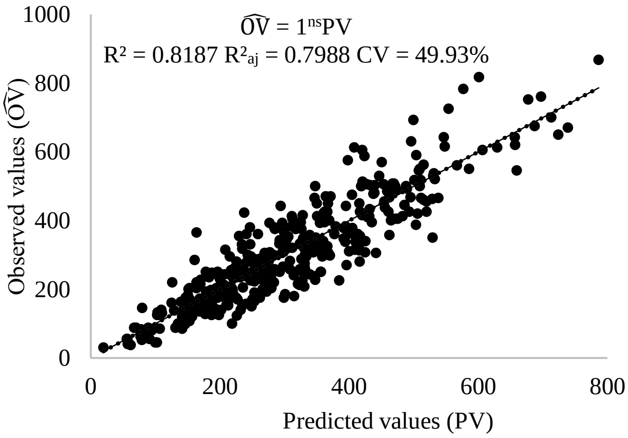
$Prod_i 10 = \beta_0 + \beta_1 CL_i + \beta_2 CW_i + \beta_3 CT_i + \beta_4 PH_i + \beta_5 NC_i + \beta_6 TCA_i + \beta_7 CL_i^2 + \beta_8 CW_i^2 + \beta_9 CT_i^2 + \beta_1 CA_i^2 + \beta_{11} NC_i^2 + \beta_{12} TCA_i^2 + \beta_{13} CL_i CW_i + \beta_{14} CLCT_i + \beta_{15} CL_i NC_i + \beta_{16} CL_i TCA_i + \beta_{17} CL_i CL_i^2 + \beta_{18} CL_i NC_i^2 + \beta_{19} CW_i CL_i^2 + \beta_{20} CW_i CA_i^2 + \beta_{21} CW_i TCA_i^2 + \beta_{22} CT_i NC_i + \beta_{23} CT_i CL_i^2 + \beta_{24} CT_i CW_i^2 + \beta_{25} CT_i CT_i^2 + \beta_{26} CT_i CA_i^2 + \beta_{27} CT_i NC_i^2 + \beta_{28} PH_i NC_i + \beta_{29} PH_i CW_i^2 + \beta_{30} PH_i CA_i^2 + \beta_{31} NC_i TCAi + \beta_{32} NC_i CW_i^2 + \beta_{33} NC_i CT_i^2 + \beta_{34} NC_i CA_i^2 + \beta_{35} NC_i NC_i^2 + \beta_{36} NC_i TCA_i^2 + \beta_{37} TCA_i CW_i^2 + \beta_{38} TCA_i NC_i^2 + \beta_{39} TCA_i TCA_i^2 + \beta_{40} CL_i^2 CW_i^2 + \beta_{41} CL_i^2 NC_i^2 + \beta_{42} CL_i^2 TCA_i^2 + \beta_{43} CW_i^2 CT_i^2 + \beta_{44} CW_i^2 CA_i^2 + \beta_{45} CW_i^2 TCA_i^2 + \beta_{46} CT_i^2 CA_i^2 + \beta_{47} CA_i^2 NC_i^2 + \beta_{48} CA_i^2 TCA_i^2 + \beta_{50} NC_i^2 TCA_i^2 + e_i$	3303.71
$Prod_i\ 11 = \beta_0 + \beta_1 CL_i + \beta_2 CW_i + \beta_3 CT_i + \beta_4 PH_i + \beta_5 NC_i + \beta_6 TCA_i + \beta_7 CL_i^2 + \beta_8 CW_i^2 + \beta_9 CT_i^2 + \beta_{10} CA_i^2 + \beta_{11} NC_i^2 + \beta_{12} TCA_i^2 + \beta_{13} CL_i CW_i + \beta_{14} CL_i CT_i + \beta_{15} CL_i CL_i^2 + \beta_{16} CL_i NC_i^2 + \beta_{17} CW_i CL_i^2 + \beta_{18} CW_i CA_i^2 + \beta_{19} CW_i TCA_i^2 + \beta_{20} CT_i NC_i + \beta_{21} CT_i CL_i^2 + \beta_{22} CT_i CW_i^2 + \beta_{23} CT_i CT_i^2 + \beta_{24} CT_i CA_i^2 + \beta_{25} CT_i CL_i^2 + \beta_{26} CT_i CW_i^2 + \beta_{27} CT_i CT_i^2 + \beta_{28} CT_i CA_i^2 + \beta_{29} CT_i NC_i^2 + \beta_{30} PH_i CW_i^2 + \beta_{31} PH_i CA_i^2 + \beta_{32} NC_i TCA_i + \beta_{33} NC_i CW_i^2 + \beta_{34} NC_i CT_i^2 + \beta_{35} NC_i CA_i^2 + \beta_{36} NC_i TCA_i^2 + \beta_{37} TCA_i CW_i^2 + \beta_{38} CL_i^2 CW_i^2 + \beta_{39} CL_i^2 NC_i^2 + \beta_{40} CL_i^2 TCA_i^2 + \beta_{41} CW_i^2 CA_i^2 + \beta_{42} CW_i^2 TCA_i^2 + \beta_{43} CA_i^2 NC_i^2 + \beta_{44} CA_i^2 TCA_i^2 + \beta_{45} NC_i^2 TCA_i^2 + e_i$	3292.14
$Prod_i\ 12 = \beta_0 + \beta_1 CL_i + \beta_2 CW_i + \beta_3 CT_i + \beta_4 PH_i + \beta_5 NC_i + \beta_6 TCA_i + \beta_7 CL_i^2 + \beta_8 CW_i^2 + \beta_9 CW_i^2 + \beta_{10} CA_i^2 + \beta_{11} NC_i^2 + \beta_{12} TCA_i^2 + \beta_{13} CL_i CW_i + \beta_{14} CL_i CT_i + \beta_{15} CL_i CL_i^2 + \beta_{16} CL_i NC_i^2 + \beta_{17} CW_i CL_i^2 + \beta_{18} CW_i CA_i^2 + \beta_{19} CW_i TCA_i^2 + \beta_{20} CT_i NC_i + \beta_{21} CT_i CL_i^2 + \beta_{22} CT_i CW_i^2 + \beta_{23} CT_i CT_i^2 + \beta_{24} CT_i CA_i^2 + \beta_{25} PH_i CW_i^2 + \beta_{26} PH_i CA_i^2 + \beta_{27} NC_i TCA_i + \beta_{28} NC_i CW_i^2 + \beta_{29} NC_i CT_i^2 + \beta_{30} NC_i CA_i^2 + \beta_{31} NC_i TCA_i^2 + \beta_{32} TCA_i CW_i^2 + \beta_{33} CL_i^2 CW_i^2 + \beta_{34} CL_i^2 NC_i^2 + \beta_{35} CL_i^2 TCA_i^2 + \beta_{36} CW_i^2 CA_i^2 + \beta_{37} CW_i^2 TCA_i^2 + \beta_{38} CA_i^2 NC_i^2 + \beta_{39} CA_i^2 TCA_i^2 + e_i$	3291.18
...	
$Prod_i 27 = \beta_0 + \beta_1 TCA_i + \beta_2 CW_i + \beta_3 CA_i^2 + \beta_4 NC_i^2 + \beta_5 TCA_i^2 + \beta_6 CL_i CW_i^2 + \beta_7 CL_i NC_i^2 + \beta_8 CW_i CL_i^2 + \beta_9 CW_i CA_i^2 + \beta_{10} CW_i TCA_i^2 + \beta_{11} CT_i CT_i^2 + \beta_{12} PH_i CW_i^2 + \beta_{13} PH_i CA_i^2 + \beta_{14} NC_i CW_i^2 + \beta_{15} NC_i CT_i^2 + \beta_{16} NC_i CA_i^2 + \beta_{17} CL_i^2 CW_i^2 + \beta_{18} CW_i^2 TCA_i^2 + \beta_{19} CL_i^2 TCA_i^2 + \beta_{20} CW_i^2 CA_i^2 + \beta_{21} CW_i^2 TCA_i^2 + \beta_{22} CA_i^2 TCA_i^2 + e_i$	3290.37

(...) – equations not shown $Prod_i$ 13…26. All model coefficients were significant ($p \leq 0{,}01$) using the t-test.

The equation $Prod_i 27$ showed the highest predictive capacity among linear, quadratic effects and all possible interactions to estimate the yield of cactus pear cv. Gigante (Table 2), with the estimated model $\widehat{Prod.}\ 27 = 9799^{**} + 9115^{*}TCA – 172.70^{*}CW – 0.127^{*}CA^2 + 3.08^{**}NC^2 – 14330^{*}TCA^2 + 376.1^{*}CLCW^2 - 2.88^{**}CLNC^2 - 12.6^{*}CWCL^2 + 0.017^{*}CWCA^2 - 1107^{**}CWTCA - 0.101^{*}CTCT^2 - 5.24^{*}PHCW^2 + 0.0105^{**}PHCA^2 - 1.83^{**}NCCW^2 +$

$0.0609^{*}NCCT^2 - 0.0053^{*}NCCA^2 + 0.219^{*}CL^2CW^2 - 0.065^{**}CW^2TCA^2 - 3.92^{***}CL^2TCA^2 - 0.00056^{**}CW^2CA^2 - 36.58^{**}CW^2TCA^2 + 0.0202^{***}CA^2TCA^2$.

Besides to the better suitability presented by the AIC, the R^2 and R^2_{aj} were superior to the other models with adjustments equal to 0.8187 and 0.7988, respectively, which denotes greater reliability and predictive safety (Figure 4).



CV - Coefficients of variation associated with observed yield data; ns - Not significant (p> 0.05) by t-test.

Figure 4. Relationship between values estimated and observed by the model $\widehat{Prod.}\ 27$, with all possible interactions for the variable of the yield of cactus pear cv. Gigante.

Similarly, to the present study, Amaral et al. (2017) made inferences about the yield of white oats in different succession systems with other forages. Among the models adjusted to estimate the yield of vegetable biomass and grains, the linear polynomial equations and quadratic regression reached the highest values of R^2_{aj}, above 0.87, with the highest values for quadratic models.

Although the model with quadratic interactions is composed of a higher number of predictive variables, they are easy to determine in the field to predict the yield of cactus pear cv. Gigante, which ensures the practical viability of the model, as it has been valued in studies on agricultural modeling (Guimarães et al., 2013, 2014; Soares et al., 2014; Mello et al., 2018).

CONCLUSION

The use of vegetative traits: total cladode area; the number of cladodes; area, length, thickness, and width of cladodes using multiple linear regression; quadratic interaction or only the variable, total cladode area, by using simple linear regression, allows the yield prediction of cactus pear cv. Gigante, with R^2_{aj} of 0.82, 0.76, and 0.74, respectively.

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CAPÍTULO III

Comparison of Methods for Harvest Prediction in ‘Gigante’ Cactus Pear

(Artigo publicado pelo Journal of Agricultural Science)

ARTIGO 3

Comparison of Methods for Harvest Prediction in 'Gigante' Cactus Pear[3]

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Abstract

Behavior analysis and plant expression are the answers the researcher needs to construct predictive models that minimize the effects of uncertainties in field production. The objective of this study was to compare the simple and multiple linear regression methods and the artificial neural networks to allow the maximum security in the prediction of harvest in 'Gigante' cactus pear. The uniformity test was conducted at the Federal Institute of Bahia, Campus Guanambi, Bahia, Brazil, coordinates 14°13′30″ S, 42°46′53″ W and altitude of 525 m. At 930 days after planting, we evaluated 384 basic units, in which were measured the following variables: plant height (PH); cladode length (CL), width (CW) and thickness (CT); cladode number (CN); total cladode area (TCA); cladode area (CA) and cladode yield (Y). For the comparison between the artificial neural networks (ANN) and regression models (single and multiple-SLR and MLR), we considered the mean prediction error (MPE), the mean quadratic error (MQE), the mean square of deviation (MSD) and the coefficient of determination (R^2).The values estimated by the ANN 7-5-1 showed the best proximity to the data obtained in field conditions, followed by ANN 6-2-1, MLR (TCA and CT), SLR (TCA) and SLR (CN). In this way, the ANN models with the topologies 7-2-1 and 6-2-1, MLR with the variables total cladode area and cladode thickness and SLR with the isolated descriptors total cladode area and cladode number, explain 85.1; 81.5; 76.3; 74.09 and 65.87%, respectively, of the yield variation. The ANNs were more efficient at predicting the yield of the 'Gigante' cactus pear when compared to the simple and multiple linear regression models.

Keywords: model, experimental, *Opuntia ficus-indica* Mill

1. Introduction

The Brazilian semi-arid region, circumscribed in the Caatinga biome, presents severe limits to plant production, mainly due to the low contents of available water in the soil for the plants (Albuquerque et al., 2018). However, even in this environment, unfavorable to plant growth and development, the cactus pear has emerged as a strategic resource in ruminant feeding (Ochoa et al., 2018) with significant levels of biomass production (Padilha Junior et

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al., 2016). For Amania et al. (2019), this productive potential is associated with several mechanisms of adaptation of the crop to adverse conditions in which the species is normally conducted.

The agronomic performance of a crop is of paramount importance to those who are dedicated to rural entrepreneurship, especially in climatic conditions of high productive risk (Nalley et al., 2016). Thus, the analysis of the behavior and expression of the cultivated materials are the answers the researcher needs to construct predictive models that minimize the effects of the productive uncertainties or the risk associated with the activity in the field (Guimarães et al., 2018).

The composition of models for harvest estimation with the 'Gigante' cactus pear is still sporadic in scientific literature. Although there are studies relating morphometric, morphogenic and production components in different cactus pear species (Padilha Junior et al., 2016) or even studies approaching morphological and their reflexes on yield (Silva et al., 2014), general literature lacks information that allows a comparison between the predictive tools related to cladode production in a practical and precise order, with direct application in the field.

Artificial neural networks (ANNs) stand out in predictive modeling (Fernandes et al., 2017), which is the supervised learning with multi-layer perceptron networks (MLP), trained with the back-propagation algorithm, the most used in the field of prediction. The ANNs are architected in three structures, in which the predictor variables make up the first layer; the hidden layer relates the number of neurons to be scaled; in sequence, the output layer receives stimuli from the hidden layer and constructs the pattern that will be the response. With many applications, the use of ANNs has intensified in agricultural modeling (Aquino et al., 2016; Azevedo et al., 2017).

Similarly, simple and multiple linear regression models have been extensively incorporated into agricultural prediction, such as in the estimation of irrigation depths (Vicente et al., 2015), reference evapotranspiration (Minuzzi et al., 2014), leaf area (Zeist et al., 2014) and yield (Bertolin et al., 2017). A comparison of these predictive models, ANNs and regressions, allows the researcher/producer to contrast the estimators in the field of modeling (Soares et al., 2014). With this, it is possible to identify a robust and consistent tool in agricultural prediction.

The objective of this study was to compare simple and multiple linear regression models and artificial neural networks to allow the maximum security in harvest prediction of 'Gigante' cactus pear.

2. Material and Methods

2.1 Experimental Characterization: Soil, Climate and Experimental Delimitation

The study was developed in the experimental field of the Baiano Federal Institute-IFBAIANO, Campus Guanambi, Bahia, Brazil, in a predominantly flat area, with soil classified as a LitolicNeosol, with the coordinates 14°13′30″ S, 42°46′5″ W and altitude of 525 m, with rainfall and average annual temperature of 670.2 mm and 25.9 °C, respectively.

The uniformity experiment with the 'Gigante' cactus pear was carried out with cladodes duly selected in the IFBAIANO matrix unit, being the preparation and curing of the seedlings in shaded conditions for 15 days. A total of 384 plants, spaced at 2.0 × 0.2 m, were designated as basic units (BUs) and circumscribed by a border with 116 plants, in a total area of 200 m².

2.2 Agronomic Characteristics Evaluated

The agronomic representation of the crop for data collection and analysis was obtained in the third production cycle, at 930 days after planting, at which the following predictive vegetative variables were measured: plant height (PH-m); cladode length (CL-cm), width (CW-cm) and thickness (CT-mm); cladode number (CN); total cladode area (TCA-cm^2); cladode area (CA - cm^2) and the yield variable to be predicted by the models-cladode yield (Y-t ha^{-1}).

2.3 Models for Harvest Prediction

In order to estimate the yield of 'Gigante' cactus pear, models of multi-layer perceptron (MLP) artificial neural networks (ANNs) with multiple neural structures were developed to describe crop yield. The most suitable models for prediction had three layers, the first with seven and six input neurons, a hidden layer with five and two neurons, and the output layer with one neuron, which represents the estimated variable.

The ANN models have as a characteristic the need of numerous trainings to express the prediction. Thus, to improve the networks, the function *mlp* of the RSNNS package with back propagation algorithm was applied, in which the synaptic weights, established during the training phase, are randomly generated in response to the reduction of the mean square error (MSE).

The training stages were sequenced in: 500 trainings, with activation in the hidden layer and output with the logistic and linear function, respectively; and 12 combinations of network architectures with 1, 2, 3, ... 9, 10, 20 and 30 neurons in the hidden layer, being each ANN architecture trained 100 times, selecting the best network by the lowest MSE value.

In order to optimize the prediction model with the maximum execution time efficiency and computational optimization, 1,000 new trainings were performed only with the ANN selected by the lower MSE, thus, avoiding numerous trainings for each network configuration.

The best ANN topology was developed using the back propagation algorithm to predict yield in ‘Gigante’ cactus pear by means of the phenotypic descriptors cladode area (CA), cladode length (CL), cladode width (CW), cladode thickness (CT), cladode number (CN), plant height (PH) and total cladode area (TCA). The ANNs were trained with the vegetative experimental data in order to reach the highest predictive capacity of fresh matter of the forage crop and the greater potential of generalization of the model for other applications.

In order to test the ANN efficiency, the phytotechnical data were divided into two groups, called training and validation, in the proportion of 80 and 20%, respectively. Thus, by the analysis of regression between estimated and observed yield in the validation sample, we evaluated the coefficient of determination (R^2) of the fitted model and the significance of the angular coefficient of the line by the t test, considering that an angular coefficient equal to one express the predictive capacity of the model by the high correspondence between the predicted and observed values.

In the simple and multiple regression analyzes, the models were fitted by the least squares procedure, with the regression models with simple effects and the multiple linear regression models with two or more predictor variables, respectively (Equation 1).

$$y_i = \beta_0 + \beta_{1\times1} + \beta_{2\times2} + ... + \beta_{k\times k} + ei \tag{1}$$

where, y_i refers to the fresh matter of cladodes based on the yield-related variables (x_i,…x_k) CA, CL, CW, CT, CN, PH and TCA. The *ei* is the error associated with i^{th}-observation, with normal and independent distribution, the constant β_0 is the intercession point of the model, and $\beta_1 + ... + \beta_{k\times k}$ represent the coefficients.

Based on the presented model, the stepwise method (Draper & Smith, 1981) was used to select the most relevant variables. In addition to this procedure, the selection criterion considered only the significant variables at the 5% significance level by Student’s t test. The Akaike Information Criterion-AIC-Equation 2(Akaike, 1974) was also considered as an adjustment quality estimator to select simple and multiple linear regression models, defined by:

$$AIC = -2 \ln (L_p) + 2p \tag{2}$$

where, $L_p$defines the maximum likelihood function of the estimated model, and p is the number of parameters associated with the model.

For the comparison between the ANNs and regression models, the mean prediction error (MPE-Equation 3), the mean quadratic error (MQE), the mean square of the deviations (MSD-Equation 4), the fitted coefficient of determination and the coefficient of determination (R^2-Equation 5),

$$EMP(\%) = \sum_i^n \frac{(X_{obs} - X_{pred}) \times 100/X_{obs}}{n} \tag{3}$$

$$QMD = \sum_i^n \frac{(X_{obs} - X_{pred})^2}{n} \tag{4}$$

where, $\Sigma_i^n$is the sum from i to n; $x_{obs}$is the fresh matter of cladode measured after harvest; $x_{pred}$is the matter estimated by the ANN and MRL models and “*n*”is the number of observations.

$$R^2 = \frac{SSReg}{TSS} = 1 - \frac{RSS}{TSS} \tag{5}$$

where, $0 \leq R^2 \leq 1$.

2.4 Statistical Analysis

The ANN and regression models were generated using the R software (R Development Core Team, 2019).

3. Results and Discussion

The vegetative variables plant height and area, width, length and thickness of the cladodes, although showing significant coefficients, are not recommended to compose the models of yield prediction due to the low correlation and, consequently, limited capacity to explain the behavior and the expression of yield, as indicated by R^2 and R^2a (Table 1). By the simple linear regression model, the isolated variable total area of cladodes allows to predict the yield with adequate values of R^2 and R^2a, and this model was also selected by the lowest estimate of AIC.

Table 1. Components of the simple linear regression model for prediction of 'Gigante' cactus pear yield by vegetative variables

Variables	Intercept	Slope	AIC	r	R^2	R^2a
TCA	-21.890	252.876	4445.291	0.8608	0.7409	0.7402
CN	-33.2014	16.2426	4551.134	0.8116	0.6587	0.6578
PH	-120.04	362.38	4840.924	0.5235	0.2740	0.2721
CA	-103.0273	1.3324	4909.228	0.3643	0.1327	0.1304
CW	-349.974	45.195	4915.467	0.3442	0.1185	0.1161
CL	-442.955	25.227	4917.611	0.3369	0.1135	0.1112
CT	178.095	9.440	4939.758	0.2468	0.0609	0.0584

*Note.*TCA: total cladode area; CN: cladode number; PH: plant height; CA: area, CW: width, CL: length and CT: thickness of the cladodes; AIC: Akaike Information Criterion; r: correlation coefficient; R^2: coefficient of determination; R^2a: adjusted coefficient of determination.

The predictive descriptors cladode number, plant height, area, width and length of cladodes were not included in the equation by multiple linear regression analysis, as this method only considers the significant variables. Soares et al. (2014) argue that the variables discarded by the method possibly exert little influence on the predicted variable. Consequently, for the multiple linear regression model, only the vegetative variables were selected for total cladode area and cladode thickness (Table 2).

Table 2. Components of the multiple linear regression model for prediction of 'Gigante' cactus pear yield by vegetative variables

Intercept	Slope								
	PH	CN	TCA	CA	CT	CL	CW	AIC	R^2	R^2a
-93.7883	-	-	247.7903	-	5.6736	-	-	4413.71	0.763	0.761

*Note.*TCA: total cladode area; CN: cladode number; PH: plant height; CA: area, CW: width, CL: length and CT: thickness of the cladodes; AIC: Akaike Information Criterion; R^2: coefficient of determination; R^2a: adjusted coefficient of determination.

The level of significance attributed to the predictor variables allows distinguishing which descriptor has the greatest influence on yield. Thus, the prediction studies aim to quantify the effect that one or more vegetative characters can cause on a response variable. In this work, the R^2a for the models selected with simple linear regression ranged from 0.6578 to 0.7402 (Table 1). The multiple linear equation added only 2% in the explanatory capacity of the model, with the R^2a of 0.761 (Table 2).

Soares et al. (2014) fitted regression models with similar R^2 when estimating the matter of bunches in 'Tropical' bananas. The coefficients of determination of the models presented in this study, such as those related to the estimation of production in other crops (Kaytez et al., 2015; Leal et al., 2015; Dornelles et al., 2018) can be considered of low magnitude, since the predictive descriptors explained in a limited way the performance of the predicted variable

After intense training for the composition of the ANNs, two architectures with the greatest potential to predict cactus pear yield were determined based on the coefficient of determination, mean square error and mean square of the deviations. The models 7-5-1 and 6-2-1 (Table 3) were selected using the criteria of relevance and greater predictive capacity. The first one had all the measured variables in the input layer (CA, CL, CW, CT, CN, PH, TCA) and five neurons in the middle layer, whereas the second estimator did not include the phenotypic descriptor CA and only had two neurons in the hidden layer.

Table 3. Statistical parameters for artificial neural network (ANN) architecture with seven and six variables in the input layer

ANNs for sampling data	7-1-1	7-2-1	7-3-1	7-4-1	7-5-1	7-6-1	7-7-1	7-8-1	7-9-1	7-10-1	7-20-1	7-30-1
	Network architecture with seven variables in the input layer											
R^2	0.687	0.723	0.710	0.766	0.851	0.749	0.769	0.699	0.809	0.791	0.751	0.762

MSE	0.011	0.009	0.007	0.010	0.004	0.011	0.010	0.008	0.007	0.006	0.010	0.006
MSD	3.05	2.919	2.467	2.818	1.977	3.029	2.773	2.499	2.523	2.285	2.662	2.158
Network architecture with six variables in the input layer												
	6-1-1	6-2-1	6-3-1	6-4-1	6-5-1	6-6-1	6-7-1	6-8-1	6-9-1	6-10-1	6-20-1	6-30-1
R^2	0.798	0.815	0.763	0.769	0.759	0.725	0.746	0.711	0.780	0.701	0.711	0.788
MSE	0.007	0.006	0.005	0.009	0.010	0.008	0.008	0.010	0.007	0.010	0.008	0.007
MSD	3.555	2.858	2.928	3.561	3.728	3.369	3.338	3.655	3.095	3.820	3.326	3.167

Note.R^2: coefficient of determination; MSE: Mean squared error; MSD: mean square of the deviations.

In addition to representing all tested network architectures, Table 3 presents the statistical parameters associated with the predictive models. Thus, the R^2, MSE and MSD markers attest to the high predictive capacity of the 7-5-1 and 6-2-1 models, with 0.851; 0.004 and 1.983 and 0.815; 0.006 and 2.858 (Table 3), respectively. The R^2 values indicate that the vegetative variables used allow explaining by 85.1 and 81.5% the productive variation of the cactus pear with the architectures 7-5-1 and 6-2-1, respectively.

Soares et al. (2014) and Leal et al. (2015) fitted the best models to estimate yield with the 10-10-1 and 4-4-1 network formats for banana and corn, in that order. Similar to the present study, the researchers emphasized that the consecutive increase in the number of neurons in the hidden layer does not represent a tendency to the best adjustment of the network, as the intense training through the combination of the synaptic weights defines the most appropriate architecture to estimate the dependent variable.

In order to predict the yield of the 'Gigante' cactus pear, the improvement of the ANNs considered an error tolerance of 0.0001, arbitrated in 500 trainings, with a learning rate of 0.1. These values, previously established, were defined in the learning process to ensure the maximum efficiency of the ANNs, since smaller values would overload the analyses without positive effect on the results (Soares et al., 2014).

Figure 1 represents the best ANN topology developed by the back-propagation algorithm to predict yield in 'Gigante' cactus pear, using the phenotypic descriptors CA, CL, CW, CT, CN, PH and TCA (Figure 1A) and the predictive model without the variable CA (Figure 1B).

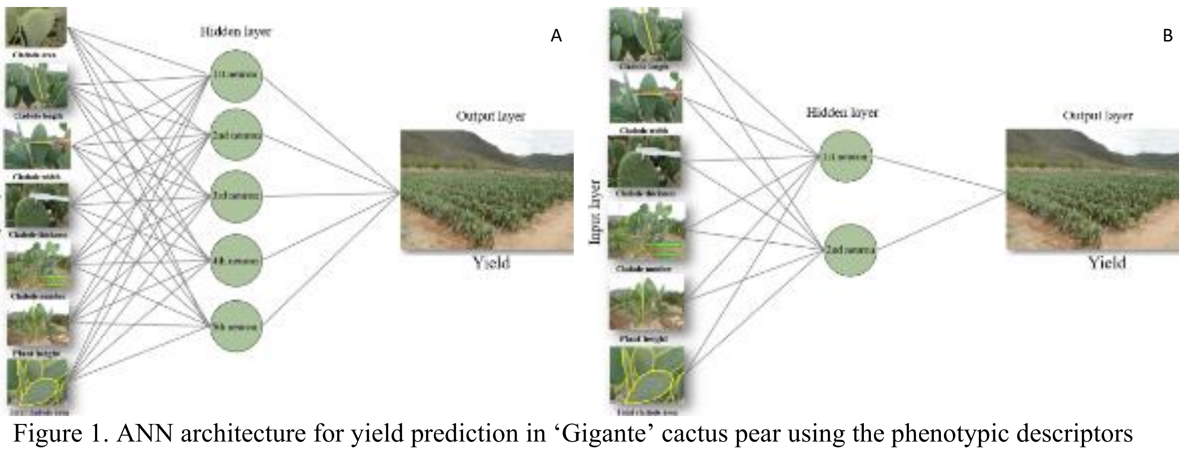

Figure 1. ANN architecture for yield prediction in 'Gigante' cactus pear using the phenotypic descriptors cladode area (CA), cladode length (CL), cladode width (CW), cladode thickness (CT), cladode number (CN), plant height (PH) and total cladode area (TCA) (A) and the predictive model without the descriptor CA (B)

After an intense training with the interconnections of the network neurons from the vegetative variables measured in the third production cycle, ANNs 7-5-1 and 6-2-1 made it possible to accurately visualize the effect of the network on the output layer-cactus pear yield. Thus, these models make it possible to predict the practical reality of the planned areas with this crop by means of the vegetative variables inserted in the input layer, as in Figure 1.

Figure 2 graphically compares the values estimated by the SLR, MLR and ANN models in contrast to the original yield data measured in the field. The estimators-SLR with the isolated variables ATC and NC; MLR with the conjugated variables ATC and CT; and ANNs with the architectures 7-5-1 and 6-2-1 were associated with the red, purple, yellow, blue and green lines, in this order; yield is represented by the black line with the field data. Thus, the closer the model lines were to the black line, the greater the accuracy and reliability of the yield forecast characteristic.

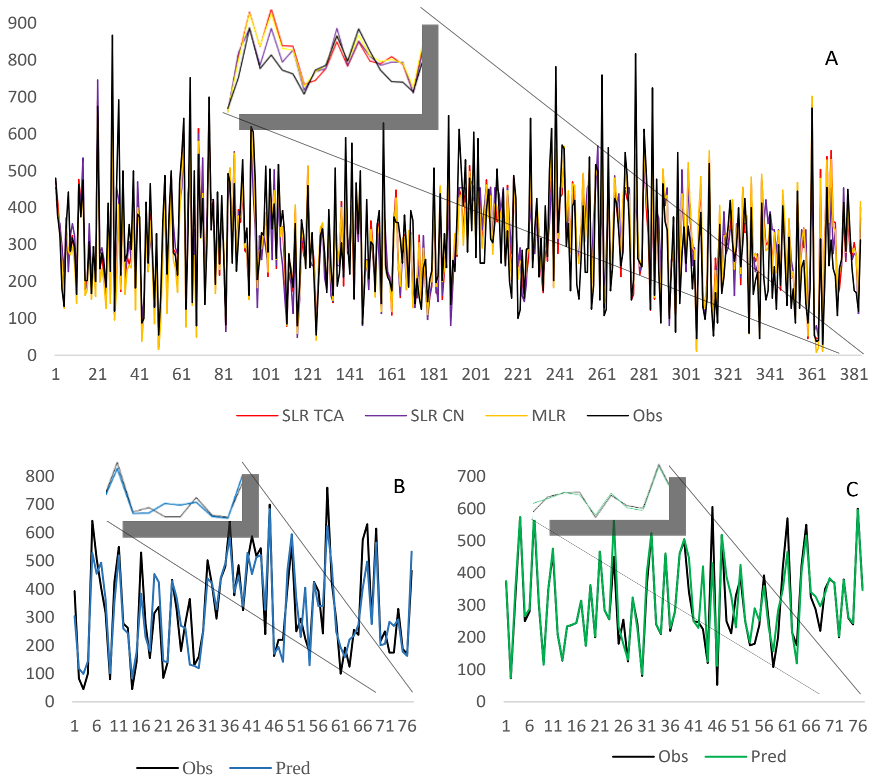

Figure 2. Graphical representation of the observed data (black), data estimated by the SLR with the variables TCA (red) and CN (purple), data predicted by MLR with the variables TCA and CT (yellow) and data predicted by ANN 6-2-1 (B-blue) and 7-5-1 (C-green) for 'Gigante' cactus pear yield prediction. We used 384 and 77 plants for the regression and ANN models, respectively. The zoom cuts contemplated ten plants for all models

The values estimated by the ANN with the architecture 7-5-1 (Figure 2C) presented the closest proximity to the data measured in the field, followed by the values estimated by ANN 6-2-1, MLR (TCA and CT), SLR (TCA) and SLR (CN). These graphical assumptions are corroborated by the coefficients of determination of the models, in which the behavior of the response variable is explained by the predictor variables. In these terms, the ANNs with the topologies 7-2-1 and 6-2-1, the MLR with the variables TCA and CT, and the SLR with the isolated variables ATC and NC explain 85.1; 81.5; 76.3; 74.09 and 65.87%, respectively, of 'Gigante' cactus pear yield variation (Table 4).

Table 4. Comparison between simple and multiple linear regression models and artificial neural networks for yield estimation in 'Gigante' cactus pear

Characteristic	SLR (CN)		SLR (TCA)		MLR (TCA & CT)		ANN 6-2-1		ANN 7-5-1	
	R^2	MPE	R^2	MPE	R^2	MPE	R^2	MPE	R^2	MPE
Yield	0.659	2.11	0.741	1.94	0.763	1.74	0.815	0.198	0.851	0.186

Note. SLR: simple linear regression; MLR: multiple linear regression; ANN: artificial neural network; R^2: coefficient of determination; MPE (%): mean prediction error.

The combination of the values predicted by the models and the original data made it possible to obtain the R^2 and the calculation of the mean error associated with the prediction (Table 4). The highest and the lowest mean errors of the prediction were associated with the SLR (NC) and ANN 7-5-1 models, respectively. In a complementary way, Figure 3 represents the accuracy of the models studied through the behavior of the respective lines, and the best fit between the observed data and the estimated values were defined with ANNs (Figure 3C). Fernandes et al. (2017) add that the superiority of this method is due to the sensitivity in the inflection rates of the progression curves, which reflects the greater predictive capacity.

For Soares et al. (2014), the prediction models with ANNs showed great potential in describing the matter of the bunch in 'Tropical' bananas, with MPE of 1.40, while multiple linear regression was fitted with MPE of 6.52. These results were similar to the present study, with the lowest prediction errors and the highest R^2 values associated to the ANNs. Hence, these can be considered as a useful tool to delineate the plant expression and behavior.

Due to the safety and efficiency of the technique in decision making, the ANNs have stood out in several lines of prediction because of the generalization capacity of the trained models in up to 100%. This predictive architecture was selected by Campos and Garcia (2019) in the format 26-12-1 and 0.0001, referring, respectively, to the number of neurons in the input layer, the hidden layer, the output layer and the mean square error. Fernandes et al. (2017) concluded that ANN modelling, although with R^2 equal to 0.61, was more effective in estimating sugarcane yield than official surveys, anticipating the harvest forecast in three months.

One of the main applications of ANNs is anchored in the prediction of phenomena (Campos & Garcia, 2019), a circumstance also related to regression models (Bertolin et al., 2017). Thus, in view of this convergence or functional similarity, some studies were developed with the objective of comparing the efficiency of ANN models with regression techniques. In the evaluations of these prediction methods in several crops such as maize (Leal et al., 2015), banana (Soares et al., 2014) and rice (Giordano et al., 2010), the authors demonstrated a higher predictive quality for ANNs in relation to the regression equations.

In addition, other studies (Campos et al., 2017; Fernandes et al., 2017;Dornelles et al., 2018) described the ANNs as robust and efficient tools with a remarkable predictive capacity, in which the historical patterns of a given data set can be projected into refined trending lines, with a view to solving problems and providing responses to decision making.

Leal et al. (2015) argue that, although the ANNs have higher computational costs, with the greater demand for the construction of networks and the need to be trained countless times at each validation step, the use of this technique, based on the clay content variables, cation exchange capacity, soil organic matter and base saturation, allows better adjustments to estimate grain yield in relation to regression estimators.

Soares et al. (2013) ratified the accuracy and efficiency of the ANN computational model in estimating yield in ‘Tropical’ bananas. Faced with the quality of the fitted model, the same authors compared ANN estimators and multiple linear regression for prediction of the same variable and found differences between the methods, similarly to the present study, with R^2 of 0.91 and 0.71, in this order, for the tested models (Soares et al., 2014).

Dornelles et al. (2018) simulated models for predicting oat grain yield through artificial intelligence and traditional polynomial regression analyses, identifying higher performance and predictive quality in fitting with the use of artificial neural networks of multiple layers. Thus, the artificial model, as it has a smaller error associated to the prediction, allows us to construct strategies to optimize the agricultural resources and to make feasible marketing plans with greater security (Leal et al., 2015).

Campos et al. (2017) have identified similarities in predictive efficiency between ANN models and the regression equations traditionally employed by forest companies. However, the models with the ANNs, similarly to the present study, presented higher coefficient of determination and smaller value in the square root of the mean error. The comparison between prediction tools in agriculture has been growing significantly, especially for providing the researcher/producer with tools to ensure maximum efficiency in decision making (Arruda et al., 2013; Soares et al., 2014; Leal et al., 2015; Dornelles et al., 2018).

The development of high-efficiency models obtained from the original field conditions favors safety when predicting ‘Gigante’ cactus pear yield (Guimarães et al., 2018), which contributes to the success of rural planning, especially as a support to the producer who needs to define in advance the quantity of animals to be fed with the produced biomass or even the volume to be marketed (Marques et al., 2017).

Thus, the solution of problems through artificial intelligence, using artificial neural networks, is quite significant and promising to support decisions in agriculture (Soares et al., 2014; Dornelles et al., 2018), promoting predictive models with superior performance compared to validated conventional tools (Arrudaet al., 2013; Kaytez et al., 2015; Leal et al., 2015).

4. Conclusions

The ANNs allow the development of more efficient models for the prediction of ‘Gigante’ cactus pear yield in comparison to the simple and multiple linear regression models, using the vegetative variables cladode area, cladode length, cladode width, cladode thickness, cladode number, plant height and total cladode area.

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CAPÍTULO IV

SIZE OF PLOTS FOR EXPERIMENTS WITH CACTUS PEAR CV. GIGANTE

(Artigo publicado pela Revista Brasileira de Engenharia Agrícola e Ambiental)

ARTIGO 4

Size of plots for experiments with cactus pear cv. Gigante[4]

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Abstract: The definition of experimental plot size is an essential tool to ensure precision in statistical analysis in experiments. The objective of this study was to estimate the plot size for the cactus pear cv. Gigante using the Modified Maximum Curvature Method, under the semi-arid conditions of Northeastern of Brazil. A uniformity test was conducted at the Federal Institute of Bahia, Guanambi Campus, Bahia state, Brazil, from 2009 to 2011. The spatial arrangement was composed of ten rows with 50 plants each, whose evaluated area was formed by the eight central rows with 48 plants per row, making 384 plants and area of 153.60 m². The following variables were evaluated: plant height; length, width and thickness of cladode; number of cladodes; total area of cladodes; cladode area and green mass yield in the third production cycle. In the evaluations, each plant was considered as a basic experimental unit (BEU), with an area of 0.4 m², comprising 384 basic units (BU), whose adjacent ones were combined to form 15 pre-established plot sizes with rectangular shapes and in rows. The characteristics total area of cladodes and green mass yield require larger plot sizes to be evaluated with greater experimental accuracy. For experimental evaluation of cactus pear cv. Gigante, plot size should be eight plants in the direction of the crop row.

Keywords: uniformity, descriptors, *Opuntia ficus-indica*

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Tamanho de parcelas para experimentos com palma forrageira cv. Gigante

Resumo: A definição do tamanho da parcela experimental configura-se como ferramenta essencial para assegurar a precisão na análise estatística em experimentos. Assim objetivou-se estimar o tamanho de parcela para a cultura da palma forrageira cv. Gigante por meio do Método da Máxima Curvatura Modificado, nas condições do Semiárido Nordestino. O ensaio de uniformidade foi conduzido no Instituto Federal Baiano, Campus Guanambi, Bahia, Brasil, no período agrícola de 2009 a 2011. O arranjo espacial foi composto por dez fileiras com 50 plantas cada, cuja área útil foi formada pelas oito fileiras centrais com 48 plantas por fileira, perfazendo 384 plantas e área de 153,60 m². Foram avaliadas as variáveis altura da planta; comprimento, largura e espessura do cladódio; número de cladódios; área total do cladódio; área do cladódio e a produtividade de massa verde no terceiro ciclo de produção. Nas avaliações, cada planta foi considerada como uma unidade experimental básica (UEB), com área de 0,4 m², contemplando 384 unidades básicas (UB), cujas adjacentes foram combinadas de modo a formar 15 tamanhos de parcelas pré-estabelecidos com formatos retangulares e em fileiras. As características área total do cladódio e produtividade de massa verde exigem maiores tamanhos de parcela para serem avaliadas com maior precisão experimental. Para avaliação experimental da palma forrageira cv. Gigante, o tamanho de parcela deve ser de oito plantas no sentido da fileira de cultivo.

Palavras-chave: uniformidade, descritores, *Opuntia ficus-indica*

INTRODUCTION

Cactus pear (*Opuntia ficus-indica* Mill.) cultivation has expanded in Brazil, especially due to the wide use of this cactus species as animal feed (Aguiar et al., 2015). In Northeast Brazil, the plant is considered as source of energy with great potential in the nutrition of ruminants and, recently, the Bahia territory has intensified the efforts towards research and production of cactus pear (Silva et al., 2016; Padilha Junior et al., 2016; Donato et al., 2017).

However, studies on this forage crop, besides presenting different experimental sizes, show oversized plots, usually defined by the experience of the researcher, based on the available resources and/or on the dimension of the experimental area (Silva et al., 2016; Padilha Junior et al., 2016; Donato et al., 2016; 2017), which justifies the need for adequate statistical planning.

The maximum modified curvature method (MMCM), through a regression equation, algebraically determines the optimal point of the plot size using the relationship between the coefficients of variation and its respective sizes (Pereira et al., 2017). With this model it is possible to minimize experimental error, optimize resources and ensure maximum precision (Cargnelutti Filho et al., 2018).

Cactus pear cv. Gigante, for being a typical cactus species, has spines in its morphological structure, which causes the researcher to work without ergonomics and sometimes under insalubrious conditions. That, associated with the exposure to full sun, aggravates the difficulties in evaluating the crop. Thus, besides the statistical significance, adequate sizes of experimental plots ensure practical viability of sampling and precision in data collection (Sousa et al., 2016).

Despite that, there are no studies in the literature on estimates of size and shape of experimental plots to evaluate phenotypic descriptors in cactus pear. Therefore, this study aimed to evaluate the optimal plot size for cactus pear cv. Gigante, under the semi-arid conditions of Northeast of Brazil.

MATERIAL AND METHODS

The study was carried out at the Federal Institute of Education, Science and Technology of Bahia, Campus of Guanambi-BA, Brazil, in the period from 2009 to 2011. The experimental field is located in the district of Ceraíma (14° 13' 30" S, 42° 46' 53" W and altitude of 525 m). The region is characterized by a hot tropical semi-arid climate (Köppen), with mean annual rainfall and temperature of 670.2 mm and 25.9 °C, respectively. The soil of the experimental area was classified as Litholic Neosol (EMBRAPA, 2013).

Uniformity test with cactus pear cv. Gigante was conducted by adopting homogeneous cultivation practices in the entire area, as recommended by Ramalho et al. (2012). Cladodes, properly prepared for planting with 15-day curing, were planted in October 2009 at 2 x 0.2 m spacing, and each plant was considered as one basic experimental unit (BEU). The spatial arrangement comprised ten rows of 50 plants each. The evaluated area was formed by the eight central rows and 48 plants per row, disregarding the plants at each end, that is, a total of 384 plants and an area of 153.60 m².

The variables plant height (PH - m); length (CL - cm), width (CW - cm) and thickness (CT - mm) of cladode; number of cladodes (NC); total area of cladodes (TAC - cm²); cladode area (CA - cm²) and cladode green mass yield (Y - Mg ha^{-1}) were evaluated in the third production cycle, 930 days after planting.

To simulate the 15 plot sizes, adjacent BEUs were combined to form rectangular plots along the crop row (Table 1).

Table 1. Number and shape of plots, number of rows and plants per row, number of basic units and total area of the plot

Identification	Number of plots	Shape	Row	Plants row^{-1}	Dimensions	Number of BEU	Area (m²)

					Width (m)	Length (m)		
A	2	Rectangular	4	48	8	9.6	192	76.80
B	3	Rectangular	8	16	16	3.2	128	51.20
C	4	Rectangular	8	12	16	2.4	96	38.40
D	6	Rectangular	8	8	16	1.6	64	25.60
E	8	Rectangular	4	12	8	2.4	48	19.20
F	12	Rectangular	8	4	16	0.8	32	12.80
G	16	Rectangular	2	12	4	2.4	24	9.60
H	24	Rectangular	4	4	8	0.8	16	6.40
I	32	Rectangular	1	12	2	2.4	12	4.80
J	48	Row	8	1	16	0.2	8	3.20
K	64	Row	1	6	2	1.2	6	2.40
L	96	Row	1	4	2	0.8	4	1.60
M	128	Row	1	3	2	0.6	3	1.20
N	192	Row	1	2	2	0.4	2	0.80
O	384	Row	1	1	2	0.2	1	0.40

BEU – basic experimental unit

The modified maximum curvature method (Lessman & Atkins, 1963), adapted by Meier & Lessman (1971), was used to algebraically estimate the point at which the curvature is maximal, which corresponds to the optimal plot size, by the exponential regression equation Eq. 1:

$$y = a/x^{b} \qquad (1)$$

where:

y - indicates the coefficient of variation;

x - represents plot size in basic units; and,

a and b - are constants suitable for the model.

The maximum curvature point was given by Eq. 2:

$$X_{mc} = \left[\frac{\hat{A}^2\hat{B}^2(2\hat{B}+1)}{\hat{B}+2}\right]^{\frac{1}{(2+2B)}} \qquad (2)$$

Where:

X_{mc} - X-axis value corresponding to the maximum curvature point, i.e., it is the estimator of optimal plot size; and,

$\hat{A}$ and $\hat{B}$ - are the respective estimates of A and B, constants suitable for the equation.

Considering that the maximum curvature point X_{mc} is defined as critical point of plot, Lúcio et al. (2012) argue that decimal transformation of this value must meet the criteria of the discrete variables, rounding off to the nearest superior integer.

Statistical determinations to estimate plot size using the modified maximum curvature method were conducted in the calculation program Excel® from Microsoft®.

RESULTS AND DISCUSSION

In the formation of the 15 plots with different sizes, there was a statistical trend of exponential model for the standard deviation ($S = 6.0285x^{0.5365}$; $R^2 = 0.9677$) and linear increase for the mean ($m = 12.351X – 0.0023$; $R^2 = 1$), with increment in the sizes of BEUs (X, in BEU) (Table 2).

Table 2. Number of plots (NP), with sizes (rows (Xr) × plants per rows (Xpr^{-1})), basic experimental units (BEUs), area and respective estimates of mean, variance (s^2), standard deviation (SD) and experimental coefficient of variation (ECV) for evaluation of yield of cactus pear cv. Gigante in uniformity test with 384 BEUs of 2 × 0.2 m (0.4 m^2)

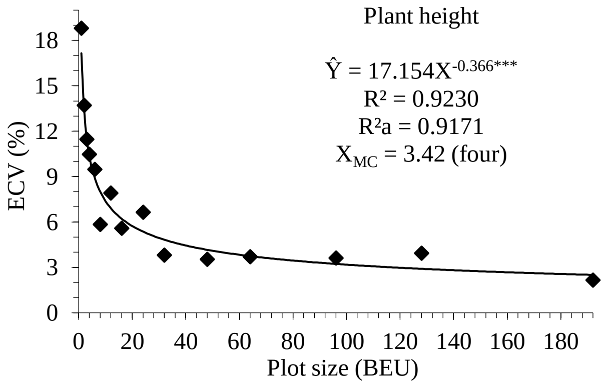
NP	Xr	Xpr^{-1}	BEUs	Area (m^2)	Mean (kg $plot^{-1}$)	S^2	SD (kg $plot^{-1}$)	ECV (%)
2	4	48	192	76.8	2371.45	8698.80	93.26	3.93
3	8	16	128	51.2	1580.97	7543.36	86.85	5.49
4	8	12	96	38.4	1185.73	5169.95	71.90	6.06
6	4	16	64	25.6	790.48	2888.75	48.15	6.09
8	4	12	48	19.2	592.86	1824.10	42.70	7.20
12	4	8	32	12.8	395.24	1102.24	33.20	8.40
16	2	12	24	9.6	296.43	2669.21	51.66	17.43
24	4	4	16	6.4	197.62	487.83	22.08	11.18
32	1	12	12	4.8	148.21	792.86	28.15	18.99
48	4	2	8	3.2	98.81	282.58	16.81	17.01
64	1	6	6	2.4	74.11	268.79	16.39	22.12
96	1	4	4	1.6	49.40	149.21	12.21	24.72
128	1	3	3	1.2	37.05	107.26	10.35	27.94
192	1	2	2	0.8	24.70	69.66	8.34	33.78
384	1	1	1	0.4	12.35	38.02	6.17	49.92

Lowest and highest experimental coefficients of variation (ECV) were respectively associated with combinations of highest and lowest numbers of BEUs (Table 2), as expected, because increasing in plot sizes usually reduces ECV, except under conditions of heterogeneous soils, in which larger plots may express higher ECV, in response to the soil heterogeneity index (Donato et al., 2018).

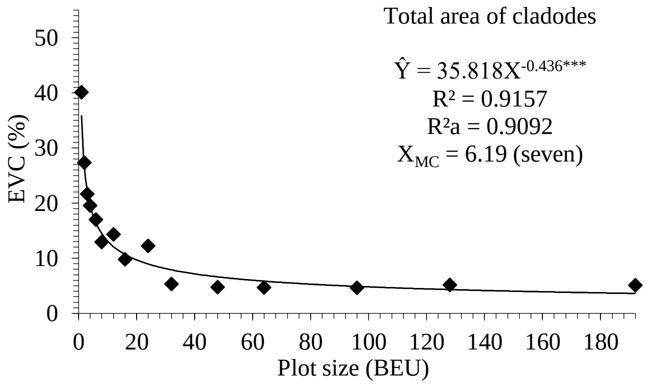
In agricultural experimentation, ECV reflects experimental precision, and plot shapes with lower estimates of this parameter are highly precise (Cargnelutti Filho et al., 2018). The relation between plot size (BEU) and ECV (Table 2) can be explained by an exponential regression equation, ECV = $49.028x^{-0.468}$; R^2 = 0.9557. Nonlinear reduction of ECV is commonly associated with BEU size both in width and length, and such inverse relation between the statistical parameters has been corroborated by several studies (Santos et al., 2015; Sousa et al., 2016; Brum et al., 2016; Cargnelutti Filho et al., 2018).

Figure 1 represents the relation between ECV and plot size in BEU. The maximum curvature point with highest estimate for the characteristics evaluated was associated with total area of cladodes (Figure 1B), followed by green mass yield (Figure 1D) with approximate plot sizes of seven and eight BEUs, respectively.

A.



B.



C.

D.

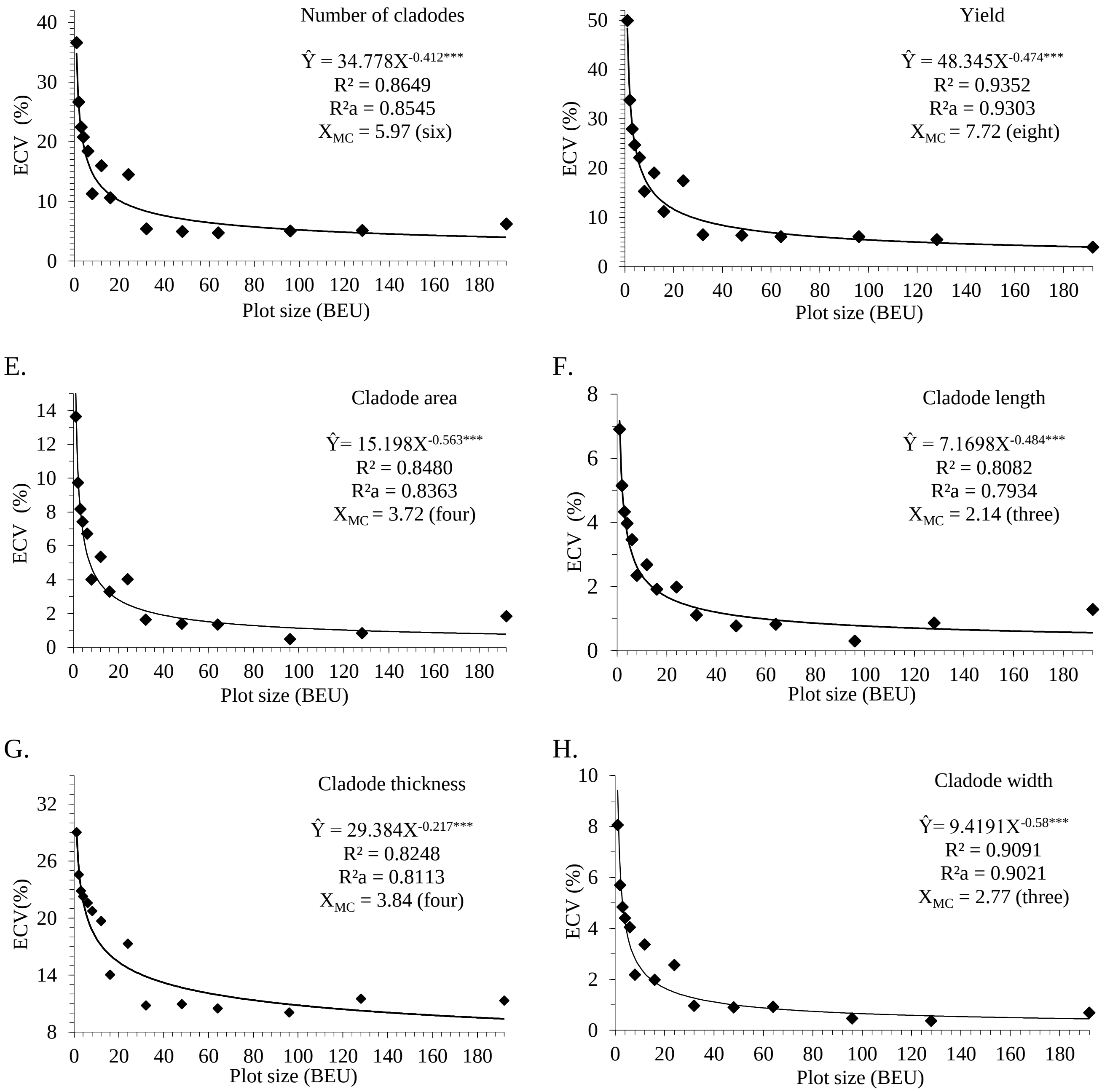


Figure 1. Relation between experimental coefficient of variation (ECV) and plot size in basic experimental unit (BEU) for the estimate of maximum curvature (X_{MC}) of the variables plant height (A), total area of cladodes (B), number of cladodes (C), yield (D), cladode area (E), cladode length (F), cladode thickness (G) and cladode width (H) of cactus pear. ***Significant ($p \leq 0.001$), by the t test.

Coefficients of determination ranged from 0.8082 (Figure 1F) to 0.9352 (Figure 1D) for the vegetative variables of cactus pear evaluated in the third production cycle. These estimates express adequate precision in the fitting of the models.

Santos et al. (2015) simulated plot sizes for different hybrids of sunflower using modified maximum curvature method (MMCM) and obtained similar fits to those of the present study, with R^2 between 0.8806 and 0.9648 for the optimal plot sizes. With this same estimator, R^2, Cargnelutti Filho et al. (2018) identified the optimal plot size (Xo, in m^2), with fit of 0.9989 to evaluate the fresh mass of forage turnip.

Optimal plot sizes varied according to the evaluated characteristics, with X_{MC} and X estimates between 2.14 and 7.72 and three and eight BEUs, respectively (Figure 1). The MMCM, besides estimating the optimal plot size pre-established by the critical point, also presents intermediate sizes among those tested, as observed in several studies (Cargnelutti Filho et al., 2014; Santos et al., 2015; Guarçoni et al., 2017).

However, when optimal plot size is achieved the continuous reduction of ECV leads to no gains in experimental precision because, from the critical or maximum curvature point, ECV tends to stability (Santos et al., 2015).

Plots with different sizes from the critical point lead to limited gains of precision, with higher experimental costs and greater demand for human resources, besides the possibility of results outside the statistical bias (Cargnelutti Filho et al., 2018). Thus, plots with practical size of three to eight BEUs were estimated, which favors decision-making with respect to precise experimental planning and adequate direction for the agronomic characteristics to be investigated.

Despite that, the largest plot size, eight BEU, must be considered for the evaluated characteristics because the characteristics observed in the study are normally evaluated together. Therefore, the largest size is selected – indicated by the characteristic with highest variability. Thus, all characteristics analyzed are met. In addition, it is justifiable to adopt this procedure because the MCMM, despite its easy application and for being of algebraic determination (Cargnelutti Filho et al., 2016), tends to determine smaller plot sizes compared to other methods (Donato et al., 2008).

CONCLUSIONS

1. The characteristics total area of cladodes and green mass yield require larger plot sizes to be evaluated with higher experimental precision.

2. For experimental evaluation of cactus pear cv. Gigante, plot size should be eight plants in the crop row direction.

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CAPÍTULO V

OPTIMAL PLOT SIZE FOR EXPERIMENTAL TRIALS WITH *OPUNTIA* CACTUS PEAR

(Artigo pela publicado pela revista Acta Scientiarum. Technology)

ARTIGO 5

Optimal plot size for experimental trials with *Opuntia* cactus pear[5]

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ABSTRACT. The objective of the study with 'Gigante' cactus pear was to determine the size of plots that optimize the implementation of experiments with greater accuracy, spatial adequacy and efficiency of use of the experimental area by the Hatheway method (1961). The experiment was conducted in a uniform spacing of 2.0 x 0.2 m with 384 basic experimental units (BEUs). The vegetative descriptors were evaluated in the third production cycle. The coefficient of experimental variation (CVe) is the factor with the greatest influence for the experimental plot design; followed by the parameters - index d, which determines the difference to be detected between treatments; by the number of replications and, finally, by the number of treatments, which has the smallest effect on the plot size (BEUs). For the efficiency of use of the experimental area - EUEA, one can select larger plots (three BEU) with a lower number of repetitions (three) or smaller plots (two UEB) with a higher number of repetitions (10) with the same level of accuracy to evaluate the yield of 'Gigante' cactus pear. However, the selection criteria are based on the smallest experimental area, reflecting the maximum of EUEA. Useful plots with eight basic units are considered efficient for experiments with cactus pear.

Keywords: agronomic descriptors; experimental accuracy; basic experimental units.

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Introduction

Due to its high nutritional and energetic and hydric value, 'Gigante' cactus pear (*Opuntia ficus-indica* Mill) stands out as a strategic food source for ruminant nutrition (Aguiar et al., 2015). Additionally, because of morphological, anatomical and physiological characteristics, this plant combines efficient mechanisms for the use of water in semi-arid conditions (Dantas, Lima, & Mota, 2017). Thus, forage production is of particular importance in the composition of balanced diets, especially in an adverse ecosystem (Aguiar et al., 2015).

Recent studies with cactus pear have been developed to optimize agricultural resources for various technological levels. These works are associated with mineral fertilization (Silva et al., 2016), organic fertilization (Donato, Donato, Silva, Pires, & Silva Júnior, 2017), economic viability of irrigated and narrow rows (Dantas et al., 2017), harvest intensity and correct harvest management (Lima et al., 2016), animal feed (Aguiar et al., 2015), among others (Guimarães, Donato, Azevedo, Aspiazú, & Silva Junior, 2018).

These studies, despite the relevance to the semi-arid region, reveal some disagreements on the experimental arrangement, number of replications and size of the experimental unit used (Queiroz et al., 2015; Padilha Junior, Donato, Silva, Donato, & Souza, 2016; Silva et al., 2016). Thus, it is necessary to improve the agricultural research with cactus pear in order to obtain information on the number of replications, size and shape of the experimental plots to achieve results that allow detecting significant differences between tested treatments (Cargnelutti Filho, Storck, Lúcio, Toebe, & Alves, 2016; Cargnelutti Filho, Araujo, Gasparin, & Foltz, 2018).

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The ideal size of the experimental plot can be established considering soil heterogeneity index - SHI (Smith, 1938; Cargnelutti Filho et al., 2016), genetic material or studied crop (Sousa, Silva, & Assis, 2016), balance between accuracy and costs (Cargnelutti Filho et al., 2016; Sousa et al., 2016), nature of the experimental material, number of replicates and evaluation methods (Cargnelutti Filho et al., 2018).

The estimation of plot sizes by the statistical proposal of Hatheway (1961) was investigated in several studies (Cargnelutti Filho, Toebe, Burin, Casarotto, & Alves, 2014; Schmildt, Schmildt, Cruz, Cattaneo, & Ferreguetti, 2016; Lavezo et al., 2017; Donato, Silva, Guimarães, & Silva, 2018) with wide recommendation for the use of smaller plots with a greater number of replications to reach the maximum experimental accuracy and, with this, a greater efficiency in the use of the area. These results reinforce the need to plan smaller and more efficient experiments on accuracy and costs. In addition, considering the essence of this method, the researcher can select convenient plot sizes, given the specific objectives, available resources and local conditions of the experimental field (Sousa et al., 2016).

However, there are no studies in the literature on estimates of the optimal experimental plot size for the evaluation of 'Gigante' cactus pear's phenotype descriptors. Thus, the objective of this study was to determine, using the Hatheway method (1961), convenient plot sizes for optimization of experiments, aiming at greater accuracy, spatial adequacy and efficient use of the experimental area.

Material and methods

The experiment was conducted at the *Instituto Federal de Educação, Ciência e Tecnologia Baiano*, Campus Guanambi, State of Bahia, Brazil. The region is located at 14° 13' 30" S, 42° 46' 53" W, at an altitude of 525 m. The climate is considered as hot tropical semi-arid, according to Köeppen classification. The soil is a Lithic Neosol and the averages for annual rainfall and temperature are, respectively, 670.2 mm and 25.9°C.

The experiment was carried out in a uniformity test with cactus pear. These blank trials are characterized by not having treatments, and maintaining homogeneous cultural treatments in any experimental area (Ramalho, Ferreira, & Oliveira, 2012). The crop was planted in a spacing of 2.0 x 0.2 m, in a format of ten rows with 50 plants each. The eight central rows, with 48 plants per row, were considered as useful area, totaling 384 plants and a 153.6 m^2 area.

In the evaluations, each plant was considered as a basic experimental unit (BEU), thus, totaling 384 BEUs. These plants were combined by configuring 15 plot sizes, pre-established with rectangular shapes, and in rows, sufficient to cover all experimental space. The vegetative descriptors evaluated were: plant height (m), length (cm), width (cm) and thickness of the cladode (mm), number of cladodes (unit), mass of cladodes (kg), area of the cladode (cm^2) and the green mass yield of each plot (mg ha^{-1}) in the third production cycle.

For the determination of the Hatheway Method (1961), entitled as the appropriate size of the experimental plot, the complete grouping of the adjacent BEUs in the field was carried out, occupying the entire evaluation area. Based on the descriptors measured in the adjacent BEUs, to compose the plot shapes, the measurements of statistical variability, soil heterogeneity index (Smith, 1938) and plot size (Hatheway, 1961) were determined by means of Microsoft - Excel® calculation worksheet, according to the model proposed by Donato et al. (2018).

Soil variability is expressed indirectly by the degree of correlation between the plot size and the variance of the adjacent BEUs, being this an inversely proportional relation. Thus, the soil heterogeneity index (b), established by the linear equation of Smith (1938), is plotted: $\log(Vx) = \log(V1) - b\,[\log(x)]$, in which: Vx, variance of the descriptors measured in the third production cycle of the cactus pear for each corresponding plot size; V_1, variance between plots with one basic unit; b, soil heterogeneity index; and x, plot size in BEU.

To estimate suitable plot sizes, Hatheway (1961) added the coefficient of variation of the evaluated descriptors to Smith's SHI method (1938), in order to align the convenient plot size with the percentage difference between the means of the treatments to be detected. Accuracy levels $\alpha_1 = 5.0\%$ and $\alpha_2 = 2\,(1 - P)$, with P = 0.80 (80% probability), were considered for four, five and six replicates; five, 10, 15 and

20 treatments; and differences to be detected between the means of treatments, d, equal to 10, 20, 30, 40 and 50%. For the application of this method, the experimental design was randomized blocks.

For the determination of plot sizes, it was considered the Equation 1:

$$x^b = \frac{2(t_1 + t_2)^2\, cv^2}{rd^2} \qquad (1)$$

where:

x is plot size (BEU); CV^2 is squared coefficient of variation (%) of plots with 1 BEU; b, is Smith's heterogeneity index; t_1 is the critical value of the Student's distribution at the α_1 probability level; critical value of the Student's distribution at the α_2 = 2 (1-P) probability level, in which P is the selected probability of obtaining a significant result; r, number of replicates; d, difference to be detected, measured as a percentage of the mean. To estimate the detectable difference between treatment means (d), it was employed the Equation 2:

$$d = \sqrt{\frac{2(t_1 + t_2)^2 cv^2}{rx^b}} \qquad (2)$$

Determined for each variable measured in the third cycle of cactus pear production, with 1, 2, 3, 4, 6, 8, 12, 16, 24, 32 and 48 BEUs, (0.4, 0.8, 1.2, 1.6, 2.4, 3.2, 4.8, 6.4, 9.6, 12.8 and 19.2 m^2). The experiments were analyzed in randomized blocks, with five and ten treatments, and 3, 4, 5, 6 and 10; and, 3, 4 and 5 replicates, respectively (Hatheway, 1961).

Results and discussion

From the estimate of the index b, soil heterogeneity described by Smith (1938), the coefficients were determined to be 0.72; 0.85; 0.79; 0.94, respectively, for the descriptors, plant height (Figure 1A), total area of cladodes (Figure 1B), number of cladodes (Figure 1C), and green mass yield (Figure 1D), evaluated in the third production cycle. According to the description, values of b> 0.70 denote soils of a heterogeneous nature, with low correlation between the adjacent basic units (Smith, 1938).

Several factors that may favor the heterogeneity of the experimental area, such as the physical-chemical characteristics of the soils, agronomic material to be tested, crop management, intra- and inter-plot competition or failures during sampling (Ramalho et al., 2012). Cargnelutti Filho et al. (2014) emphasize that the experimental accuracy is mainly affected by soil heterogeneity and the material analyzed.

The regression coefficients 1.04; 0.94; 0.40 and 1.14 were associated with the variables area (Figure 2A), length (Figure 2B), thickness (Figure 2C) and width of cladodes (Figure 2D), respectively. The index b, because it is a negative value, must be considered in module. Normally, these values do not extrapolate a unit, as verified for these last two characteristics. However, it can be assumed, based on Donato et al. (2018), that the b estimation method is inserted into the category $0 < b < +\infty$. Thomas (1974) interprets the index b>1 as the reflection of the negative correlation between the confronting plots, if each plot is composed of a single BEU. Sousa et al. (2016) state that this argument is incomprehensible when the plot is formed by more than one BEU, since, normally, blank experimentation suggests competition between BEUs or high susceptibility of plants to environmental variations.

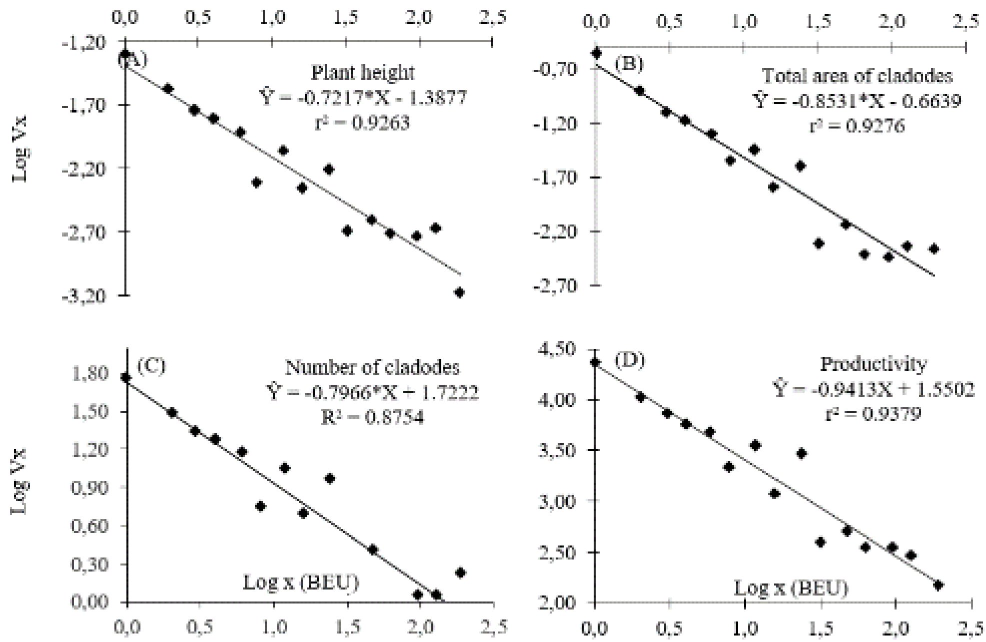

Figure 1. Regression equations between logarithm of variance and logarithm of plot size (BEU), for plant height (A), total area of cladodes (B), number of cladodes (C) and green mass yield (D), evaluated in the third production cycle in 'Gigante' cactus pear. ()Non-significant (p > 0.05); *significant with (p ≤ 0.05), by the t test.

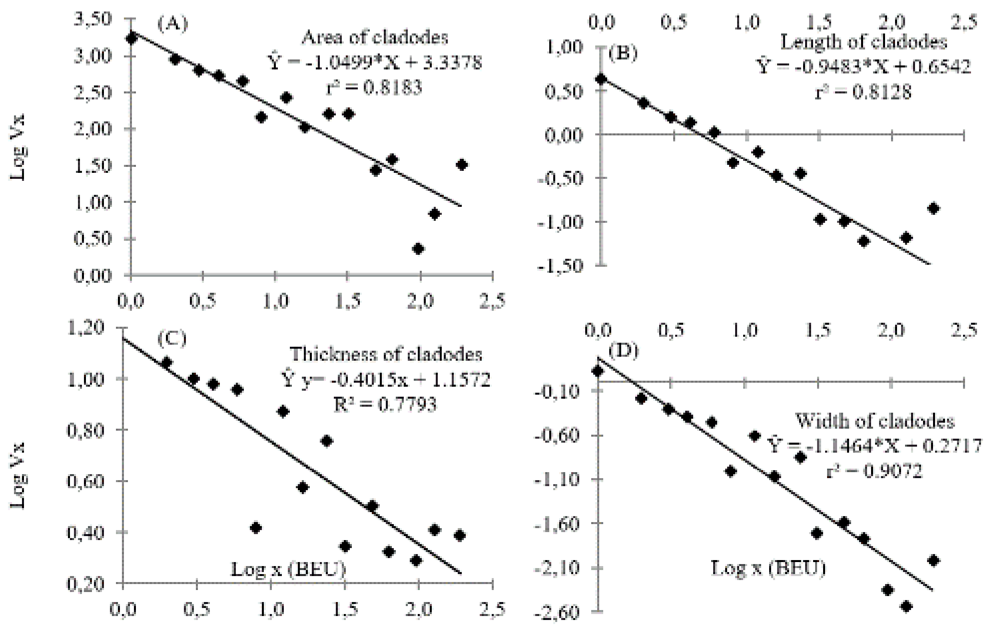

Figure 2. Regression equations between logarithm of variance and logarithm of plot size (BEU) for mean characteristics area of cladodes (A), length of cladodes (B), thickness of cladodes (C) and width of cladodes (D), evaluated in the third production cycle in 'Gigante' cactus pear. ()Non-significant (p > 0.05); *significant with (p ≤ 0.05), by the t test.

In a similar study with the sunflower crop, Sousa et al. (2016) estimated an index b at 1.0585 for all cultivars tested, thus denoting high soil variability, through the nullity of correlation between the BEUs. Also, in this context, indices b > 1 have been observed in several agronomic studies (Lúcio, Haesbaert, Santos, Schwertner, & Brunes, 2012; Santos, Haesbaert, Lúcio, Storck, & Cargnelutti Filho, 2012; Donato et al., 2018).

According to Lavezo et al. (2017), the experimental design, applied in an efficient way, seeks to promote the adequate arrangement between statistical factors, treatments, replicates and plot size, in order to optimize the experimental area and achieve maximum accuracy for the evaluated parameters.

Based on the Hatheway method (1961), a statistical matrix was obtained, making it possible to identify the ideal combination in the experimental plan between the vegetative characteristics (Table 1).

The coefficients of experimental variation (CVe) reflect the natural and specific variability in the evaluated characteristic. However, it can be influenced mainly by the soil conditions and the agricultural management of the BEU, which directly influences the experimental accuracy (Cargnelutti Filho et al., 2018). Pimentel-Gomes (2009) classified the experimental accuracy using CVe, so that values lower than 10%, between 10 and 20%, between 20.01 and 30% and greater than 30%, indicate, in this order, high, medium, low and very low experimental accuracy.

In this study, among the eight characteristics evaluated, the CVe values oscillated between 6.89 and 50.13% (Table 1), for the vegetative and yield characteristics. In 50, 12.5 and 37.5% of the evaluated parameters, CVe values were classified as very low, medium and high at the same time (Pimentel-Gomes, 2009).

The CVe had a directly proportional relationship to the plot size, as expected, since the greater percentage variation of the evaluated characteristic indicates the need for a larger experimental area to detect a significant difference between the treatments (Cargnelutti Filho et al., 2018).

Thus, CVe is the factor with the greatest influence on the experimental plot dimension, followed by the index d, which determines the difference to be detected between treatments; the number of replicates and, finally, the number of treatments, with smaller effect on the plot size. Similar sequence on the order of importance of the factors was reported by Sousa et al. (2016), Oliveira, Mello, Lima, Scolforo, and Oliveira (2011), Muniz, Aquino, Simplicio, and Soares (2009) and Donato et al. (2018) for sunflower, candeia, eucalyptus and banana crops, respectively.

For the variables yield and cladode length, considering values close to the soil heterogeneity index b = 0.9413 (Figure 1) and b = 0.9483 (Figure 2), with the factors set at d = 10%, t = 5 treatments and r = 4 replicates, the composition of 151.62 and 2.22 basic units is visualized, in this sequence, to detect the mean difference between the treatments of the aforementioned characteristics. It is worth considering that such discrepancies between the sizes of the BEUs are reflections of the CVe of the evaluated characteristic.

Table 1. Estimates of plot size, in BEU, for the characteristics evaluated in the third production production cycle in 'Gigante' cactus pear, for the combinations of number of replicates (r), treatments (t), percentual difference of the mean to be detected (d) and values of coefficient of experimental variation (CVe).

	d	CVe (%)	r = 4				r = 5				r = 6			
			t =5	t = 10	t = 15	t = 20	t = 5	t = 10	t = 15	t = 20	t = 5	t = 10	t = 15	t = 20
PH	10	18.69	45.39	41.25	39.99	39.38	31.75	29.58	28.91	28.58	23.97	22.66	22.25	22.05
	20	18.69	6.65	6.04	5.86	5.77	4.65	4.33	4.23	4.19	3.51	3.32	3.26	3.23
	30	18.69	2.16	1.96	1.90	1.88	1.51	1.41	1.38	1.36	1.14	1.08	1.06	1.05
	40	18.69	0.97	0.89	0.86	0.84	0.68	0.63	0.62	0.61	0.51	0.49	0.48	0.47
	50	18.69	0.52	0.48	0.46	0.46	0.37	0.34	0.33	0.33	0.28	0.26	0.26	0.25
TAC	10	39.96	149.7	138.1	134.5	132.8	110.7	104.2	102.2	101.2	87.2	83.2	81.9	81.3
	20	39.96	29.49	27.20	26.49	26.15	21.79	20.53	20.13	19.94	17.18	16.38	16.13	16.01
	30	39.96	11.40	10.51	10.24	10.11	8.42	7.93	7.78	7.71	6.64	6.33	6.24	6.19
	40	39.96	5.81	5.36	5.22	5.15	4.29	4.04	3.96	3.93	3.38	3.23	3.18	3.15
	50	39.96	3.44	3.17	3.09	3.05	2.54	2.40	2.35	2.33	2.01	1.91	1.88	1.87
NC	10	36.50	170.2	156.0	151.7	149.6	123.1	115.5	113.1	111.9	95.4	90.7	89.2	88.5
	20	36.50	29.86	27.38	26.62	26.25	21.60	20.26	19.84	19.64	16.74	15.91	15.65	15.52
	30	36.50	10.79	9.89	9.62	9.49	7.80	7.32	7.17	7.09	6.05	5.75	5.66	5.61

	40	36.50	5.24	4.80	4.67	4.61	3.79	3.56	3.48	3.45	2.94	2.79	2.75	2.72
	50	36.50	2.99	2.74	2.67	2.63	2.16	2.03	1.99	1.97	1.68	1.59	1.57	1.56
	10	50.13	151.6	140.9	137.6	135.9	115.3	109.2	107.3	106.3	92.9	89.0	87.8	87.2
	20	50.13	34.77	32.31	31.55	31.18	26.43	25.04	24.60	24.38	21.31	20.41	20.13	19.99
P	30	50.13	14.69	13.65	13.33	13.17	11.17	10.58	10.39	10.30	9.00	8.62	8.50	8.44
	40	50.13	7.97	7.41	7.23	7.15	6.06	5.74	5.64	5.59	4.89	4.68	4.61	4.58
	50	50.13	4.96	4.61	4.50	4.45	3.77	3.57	3.51	3.48	3.04	2.91	2.87	2.85
	10	13.58	7.50	7.02	6.87	6.80	5.86	5.59	5.50	5.46	4.83	4.65	4.59	4.56
	20	13.58	2.00	1.87	1.84	1.82	1.57	1.49	1.47	1.46	1.29	1.24	1.23	1.22
CA	30	13.58	0.92	0.87	0.85	0.84	0.72	0.69	0.68	0.67	0.60	0.57	0.57	0.56
	40	13.58	0.53	0.50	0.49	0.48	0.42	0.40	0.39	0.39	0.34	0.33	0.33	0.33
	50	13.58	0.35	0.33	0.32	0.32	0.27	0.26	0.26	0.25	0.23	0.22	0.21	0.21
	10	6.89	2.22	2.07	2.02	2.00	1.69	1.61	1.58	1.56	1.37	1.31	1.29	1.28
	20	6.89	0.52	0.48	0.47	0.46	0.39	0.37	0.37	0.36	0.32	0.30	0.30	0.30
CC	30	6.89	0.22	0.20	0.20	0.20	0.17	0.16	0.16	0.15	0.13	0.13	0.13	0.13
	40	6.89	0.12	0.11	0.11	0.11	0.09	0.09	0.08	0.08	0.07	0.07	0.07	0.07
	50	6.89	0.07	0.07	0.07	0.07	0.06	0.05	0.05	0.05	0.05	0.04	0.04	0.04
	10	28.96	8418	7089	6704	6522	4428	3900	3741	3665	2671	2415	2337	2299
	20	28.96	266.5	224.4	212.3	206.5	140.2	123.4	118.5	116.1	84.59	76.49	74.01	72.80
CT	30	28.96	35.38	29.79	28.18	27.41	18.61	16.39	15.72	15.40	11.23	10.15	9.82	9.66
	40	28.96	8.44	7.11	6.72	6.54	4.44	3.91	3.75	3.68	2.68	2.42	2.34	2.31
	50	28.96	2.78	2.34	2.21	2.15	1.46	1.29	1.23	1.21	0.88	0.80	0.77	0.76
	10	8.03	2.53	2.38	2.34	2.31	2.02	1.93	1.91	1.89	1.69	1.63	1.62	1.61
	20	8.03	0.76	0.71	0.70	0.69	0.60	0.58	0.57	0.56	0.51	0.49	0.48	0.48
CW	30	8.03	0.37	0.35	0.34	0.34	0.30	0.28	0.28	0.28	0.25	0.24	0.24	0.24
	40	8.03	0.23	0.21	0.21	0.21	0.18	0.17	0.17	0.17	0.15	0.15	0.14	0.14
	50	8.03	0.15	0.14	0.14	0.14	0.12	0.12	0.11	0.11	0.10	0.10	0.10	0.10

EC = evaluated characteristic; P = Yield; PH = Plant height; NC = number of cladodes; TAC= Total area of cladodes; CA = Cladode area; CC = Cladode length; CT = Cladode thickness; CW = Cladode width.

Equivalent proportion between the assessed characteristic, CVe and plot size was determined by Cargnelutti Filho et al. (2014), Sousa et al. (2016) and Donato et al. (2018), for turnip, sunflower and banana crops, respectively. This shows that the researcher can make use of experimental plots according to focus, model, arrangement and purpose of the research. In addition, the researcher must be careful about the size of plots estimated by the Hatheway model (1961), since some combinations of factors (CVe, d, t and r) can result in extreme plot sizes with low practical application (Sousa et al., 2016).

In this respect, it can be observed when the detectable difference in the number of cladodes and plant height is set at 10% (Table 1), because of the high discrepancy between the CVe of these characteristics (36.50 and 18.69%), despite the similarity between index b 0.7966 (Figure 1C) and 0.7217 (Figure 1A) and number of treatments (five) and repetitions (four), reflected in the extreme composition of 170.22 and 45.39 basic units (Table 1), in this sequence.

The inverse is true when we consider variables with closer CVe and index b, both for the number of cladodes (CVe = 36.50%, b = 0.7966, BEU = 170.16) and total area of cladodes (CVe = 39.96%, b =

0.8531 and BEU = 149.74), as for the variables cladode length (CVe = 6.89%, b = 0.9483 and BEU = 2.22) and cladode width (CVe = (Table 1), for the same values of d = 10%, t = 5 treatments and r = 4 replicates, the formation of basic units is similar.

The dimensioning of the plots from the basic unit formation components, CVe, index b, d, t and r, establishes similarity between the variables, mainly due to the influence of the CVe and the difference to be detected - d, since it configures a direct relationship between the variability of the data and the size of the plot (Smith, 1938; Hatheway, 1961), a fact supported in several studies (Schmildt et al., 2016; Sousa et al., 2016; Lavezo et al., 2017; Cargnelutti Filho et al., 2018). However, the lower required experimental accuracy - d, implies reduced BEUs.

Among the factors for dimensioning the basic experimental units, the number of replicates stands out with singular importance, as it directly reflects the accuracy and the experimental arrangement to be used. For this parameter, there is a direct effect between the increase in number of replicates and the decrease in plot size. On the other hand, the increase in the number of treatments showed no similar effect. While the addition of two replicates, from four to six, decreased the basic units by 38.71% (151.62 to 92.92 BEU), the increase from five to 20 treatments reduced only 10% the basic units, 151.62 to 135.98 BEU, for green mass yield (Table 1).

With this practice, it is possible to achieve greater experimental efficiency in the detection of percentage differences between treatments with smaller plots and greater number of replications, instead of larger plots and fewer replicates (Sousa et al., 2016). Cargnelutti Filho et al. (2016) argue that the increase in number of replicates is effective to enhance experimental accuracy, provided that the soil heterogeneity index ($b < 0.2$) is observed.

Also, in relation to plant height, number of cladodes, total area of cladodes and yield of green mass, it can be highlighted, in this order, a reduction of 47.19; 43.92; 41.74 and 38.71% in the number of BEUs, respectively, by adding two replicates, from four to six (Table 1). This same analysis, for thickness, length, area and cladodes width, showed decreases of the BEUs similar to the direct variables, with values of 31.73; 38.28; 35.60 and 33.20%, respectively (Table 1).

Low expression was observed in the reduction of the BEU by increasing the number of treatments, with similar mean values for all evaluated characteristics. However, when analyzing the addition of treatments by replicate category, there was a decrease in treatment effect with increasing number of replicates, with mean reduction values of 11.64, 8.83 and 7.21% of the BEUs for the four, five and six replicate levels, sequentially.

The vegetative variables plant height and cladode area (Table 1), when subjected to an increase in the number of replicates, from four to six, presented the best adjustments in the decrease of plots, 45.39 to 23.97 and 7.50 to 4.83 basic units, in that order. A similar efficacy was also found by several researchers (Oliveira et al., 2011; Sousa et al., 2016; Donato et al., 2018).

For yield, the experimental evaluation with 15 (Queiroz et al., 2015), 32 (Silva et al., 2016) and 36 basic units (Padilha Junior et al., 2016) are frequently carried out in experiments with cactus pear. However, Donato et al. (2018) describe that excessive size, especially without focus on the tested effect, maximizes costs in implementation of the experiment, without significant gains in experimental accuracy. Nevertheless, plots equivalent to $^1/_2$, $^1/_4$ and $^1/_5$ of the aforementioned sizes, respectively, provide the same accuracy, with expressive optimization of the experimental resources.

These and other relationships with the studied variables can be observed in Figure 3 and 4, with the arrangements of five and 10 treatments and five replicate levels, three, four, five, six and 10, even for the most discrepant descriptors - yield of green mass (Figure 3) and mean cladode thickness (Figure 4).

Differences of 50, 30 and 15% between treatment means can be detected with two, five and eight basic units, respectively (Figure 3 and 4). However, significant differences below 15% are not achieved with the increase in the number of BEUs, or even, there is little effect on distinguishing treatments with the addition of BEUs. For the analyzed variables, plots larger than eight BEUs do not guarantee experimental accuracy.

Regarding yield, height, number of cladodes and total area of cladodes, the plots with eight BEUs allow to visualize, in this order, 11 ± 0.4, 5.2 ± 1.2, 10 ± 3 and 10 ± 3% of variation between treatment means. The intraclass variation (±) occurs as a function of the number of replicates to be adopted in the experiment
(Figure 3).

As for the characteristics length, width and thickness of the cladode, high stability is observed for the first variables, and low uniformity for the latter (Table 1). This phenotypic behavior has a direct influence on the size of the plot to be used in the field, in addition to allowing the researcher to detect smaller (length - 6.89% and width - 8.03%) or larger (thickness – 28.96%) differences, for the same number of BEUs (Figure 4).

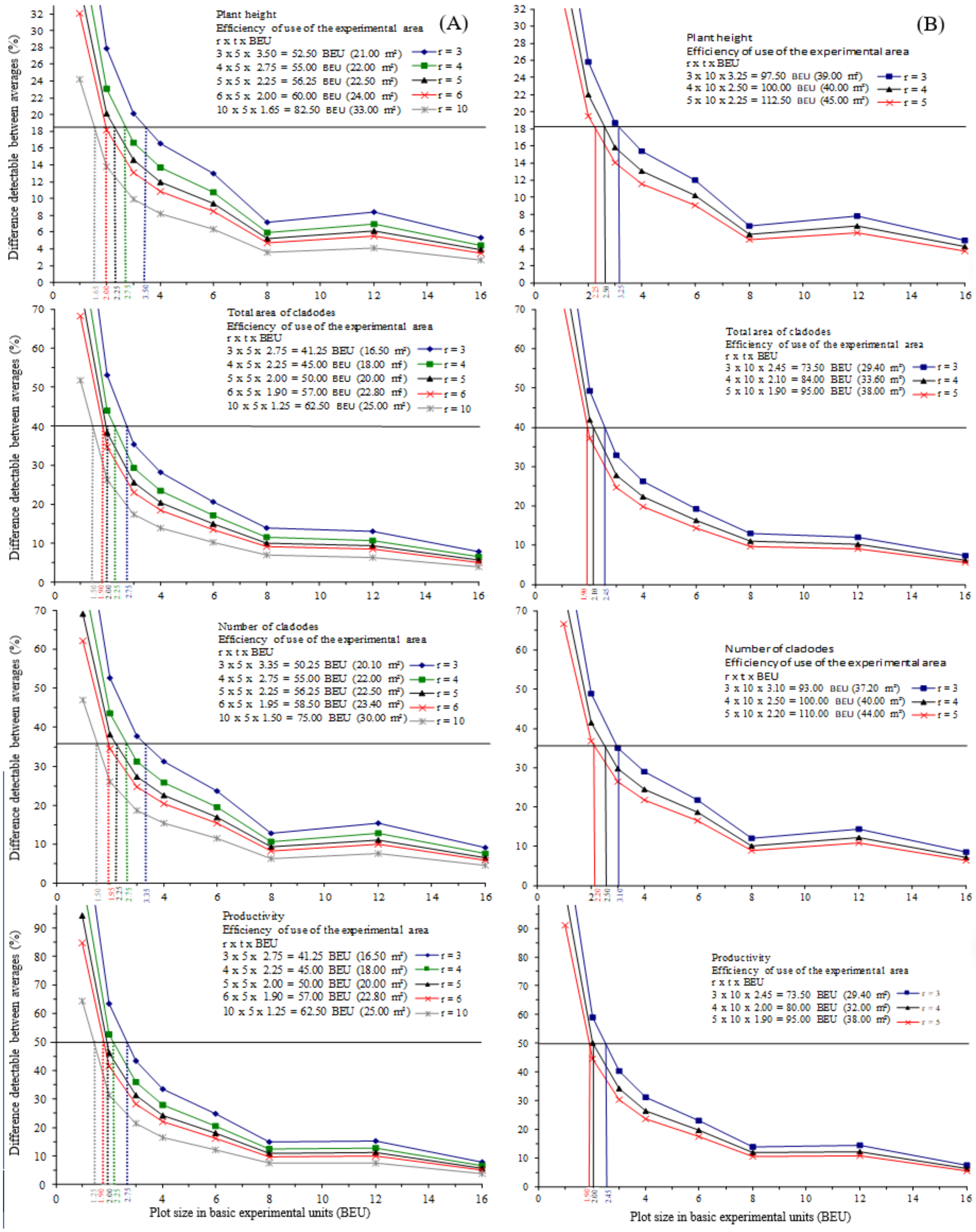

Figure 3. Relationship between plot size and detectable difference between two treatments (% of means), with five replicate options and five treatments (A) and three replicate options and ten treatments (B), for the characteristics plant height, total area of cladodes, number of cladodes and yield, evaluated in the third production cycle in 'Gigante' cactus pear.

For the aforementioned variables, when setting the size of the BEUs at eight, it is possible to obtain minimum differences between treatment means of 1.8 ± 0.4, 1.2 ± 0.4 and 15 ± 5%, for length, width and thickness of cladodes, respectively. The intraclass variation (±) occurs as a function of the number of replicates to be adopted in the experiment (Figure 4).

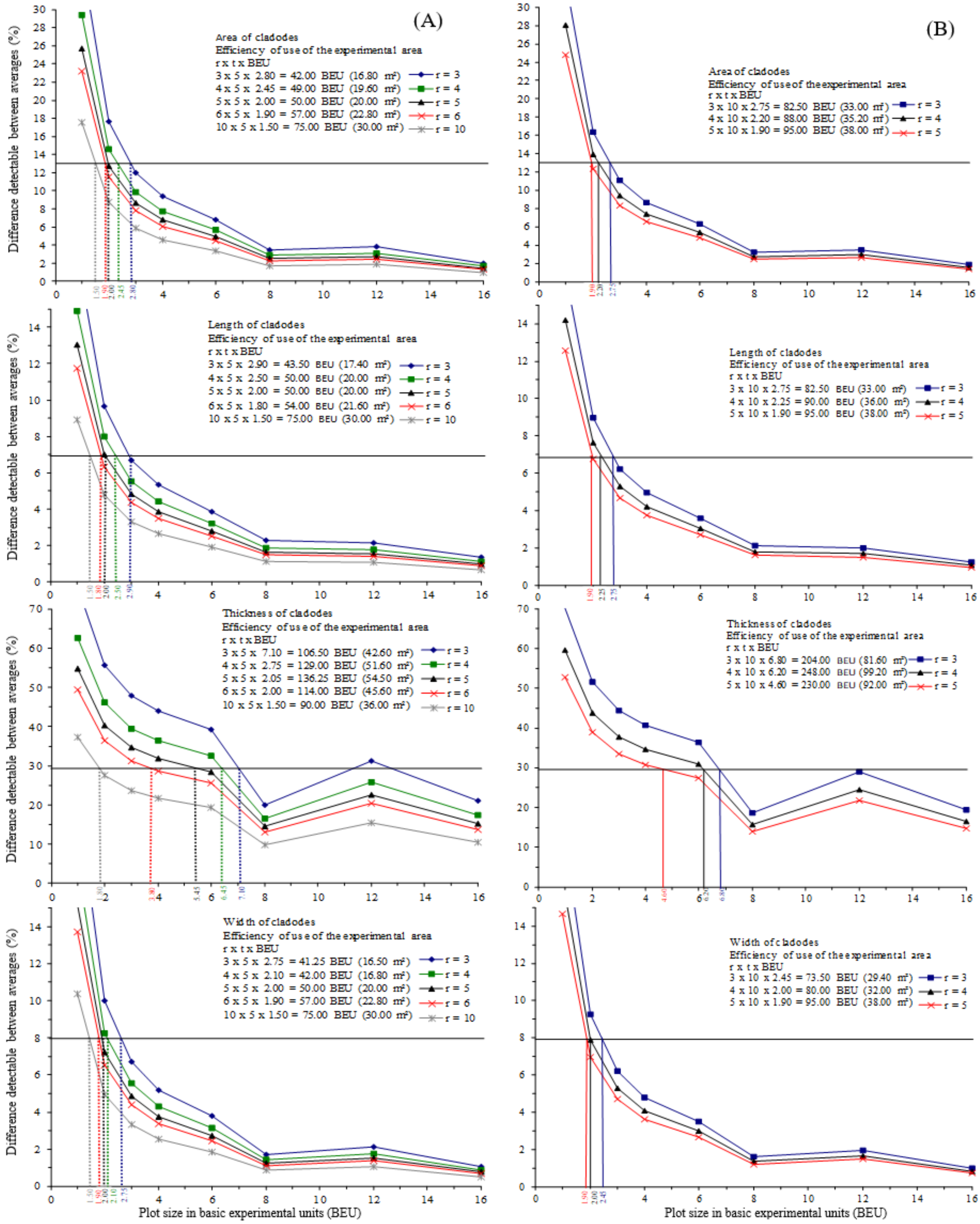

Figure 4. Relationship between plot size and detectable difference (% of means) between two treatments, with five replicate options and five treatments (A) and three replicate options and ten treatments (B), for the means of the characteristics cladode area, cladode length, cladode thickness and cladodes width, evaluated in the third production cycle of 'Gigante' cactus pear.

Table 1 and Figure 3 and 4 provide the researcher with information that is relevant to agricultural planning, especially as to the level of accuracy to be achieved in the experimental area, based on the arrangement between plot size and number of replicates. In order to select these statistical parameters, it should be observed the appropriate size of the unit to be evaluated, in terms of area, sampling, inputs, human and financial resources, as well as the requirements for number of degrees of freedom and residue (Pimentel-Gomes, 2009).

Furthermore, as a support for the diverse agricultural trials with *Opuntia* cactus pear, Figure 3 and 4 provide the analysis of the efficiency of use of the experimental area - EUEA. Therefore, the descriptors measured in the third production cycle were estimated. In this plan, the BEUs and the number of replicates were organized to detect a difference (d) of 50.13, 18.69, 36.50 and 39.96% of the mean for the variables green mass yield, height, number of cladodes and total area of cladodes, respectively. With respect to the variables related to the cladode, the difference (d) of 13.58, 6.89, 28.96 and 8.03% of the mean for area, length, thickness and width were considered in this sequence. By the specificity of the methodology proposed by Hatheway (1961), the detectable difference between the means of the treatments should be greater than the CVe.

Conclusion

1) The numerous basic experimental units, obtained through combinations of plot size and number of replicates, allow the researcher efficient planning and experimental evaluations in *Opuntia* cactus pear.

2) Useful plots with eight basic units are considered efficient for experiments with cactus pear.

3) Larger plots (three BEU) with fewer replicates (three) or smaller plots (two BEU) with a higher number of replications (ten) can be selected with the same level of accuracy to evaluate the yield of 'Gigante' cactus pear.

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CAPÍTULO VI

PLOT SIZE BY THE VARIANCE COMPARISON METHOD FOR WITH 'GIGANTE' CACTUS PEAR

(Artigo publicado pelo Journal of Agriculture Science)

ARTIGO 6

Plot size by the variance comparison method for with 'Gigante' cactus pear[6]

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Plot size by the variance comparison method for with 'Gigante' cactus pear

Abstract

Appropriate plot size is recognized as a means of maximizing experimental accuracy and contributes to efficient treatment assessment. This study aimed to estimate the optimal plot size for experiments with 'Gigante' cactus pears using the comparison of variances method (CVM). A uniformity trial was conducted to assess plant height (PH), number of cladodes (NC), yield (Y), cladode area index (CAI), cladode length (CL), width (CW) and thickness (CT), and cladode area (CA) in a cactus pear crop. A rectangular-shaped plot consisting of 10 rows of 50 plants each was used, totaling 500 plants and 384 plants, corresponding to the study area. A hierarchical classification approach was adopted, simulating a split-plot design in which each plant was denominated a basic unit (BU), and considering the effects of blocks (B), plots (P)/B, subplots (S)/P/B, rows (R)/S/P/B and plants (Pln)/F/S/P/B. This resulted in five plot sizes, consisting of 1, 12, 24, 48 and 96 basic units. Plots with 12, 24, 48 and 96 BU were statistically equal for the variables Y, PH, NC, CAI, CL, CW and CT, with lower variances than the plot with 1 BU. As such, 4.8 m² with 12 basic units is the optimal experimental plot size for 'Gigante' cactus pears.

Keywords: *Opuntia*, estimate, hierarchical model, experimental unit.

1. Introduction

The 'Gigante' cactus pear is well adapted to the conditions in Brazilian semiarid regions and an important strategic resource for animal nutrition, particularly during drought (Aguiar et al., 2015). Its high yield potential, nutritional value, drought tolerance, water use efficiency and hardiness have prompted its extensive incorporation in production arrangements and inclusion in field research (Ochoa et al., 2018; Amania et al., 2019) to better understand the plant and its potential.

In this type of research, farming experiments are the bridge between challenges and prospects for agriculture (Sampaio Filho et al., 2019). Correct plot sizes are key to minimizing experimental error and ensuring a successful design (Facco et al., 2018), which has been established in previous studies using easy-to-apply and efficient methods (Brum et al., 2016; Guarçoni et al., 2017; Cargnelutti Filho et al., 2018).

To provide an effective experimental assessment, researchers must be able to statistically differentiate between treatment effects. This depends on a range of factors, including data collection, soil heterogeneity and climate conditions (Guarçoni et al., 2017). However, the appropriate plot size and number of repetitions are more important, especially when the difference between treatments is minimal.

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Establishing the optimal plot size is therefore an integral part of planning and implementing an experiment small plots and a high number of replicates are typically linked to greater accuracy than large plots and few repetitions (Henriques Neto et al., 2009).

An accurate plot size supports the experimental design for a specific crop under certain conditions, thereby preventing generalization of the estimated model. This is in line with Facco et al. (2018), who argued that plant behavior is significantly influenced by soil and climate factors, which can negatively affect experimental accuracy if a suboptimal plot size is used.

In this respect, the comparison of variances method (CVM) has been widely used to determine the ideal plot size for different crops (Henriques Neto et al., 2009). According to Vallejo & Mendonza (1992), CVM involves estimating the variances of different plot sizes and comparing them using Bartlett's test. The smallest plot size in a group of plot sizes with similar variances is considered the optimal size for the experiment (Ortiz, 1995).

The present study aimed to estimate the optimal plot size for experiments with 'Gigante' cactus pears using the comparison of variances method (CVM).

2. Material and Methods

2.1 Experimental design

The trial was conducted with the 'Gigante' cactus pear (*Opuntia ficus-indica* Mill), from 2009 to 2011, in the experimental area belonging to the Federal Institute of Bahia (IFBAIANO) at the Guanambi Campus, in Ceraíma, Bahia state, Brazil (14°13'30" S, 42°46'53" W, altitude of 525 m). The climate in the region is classified as warm tropical semiarid, according to Köppen's classification, with an average temperature of 25.9 °C and average annual rainfall of 670.2 mm. The soil was classified as lithic neosol (EMBRAPA, 2013), with a predominantly flat relief. Based on the principle of a uniformity trial, homogeneous treatments were applied across the entire experimental area. The soil was prepared by subsoiling, plowing, harrowing and furrow opening according to predefined row spacing. Organic fertilizer was applied in-furrow and to topsoil before the rainy season, at 360 and 720 days after planting (DAP), using 60 Mg ha^{-1} year^{-1} of fresh sheep manure. The remaining crop treatments were in line with recommendations for forage plants under dry conditions (Ramalho et al., 2012).

The material used for planting was obtained from a cactus plantation at IFBAIANO, used for seed production. Cladodes were selected from the middle portion of the plants, based on maximum morphological similarity between the propagators. Prior to selection, the cladodes were placed in shade for 15 days to dehydrate and allow the injuries caused by cutting to heal.

The chosen cladodes were planted 0.2 m apart, with 2.0 m between rows and the largest surface facing east-west. The experimental area was rectangular and contained 10 rows of 50 plants, totaling 500 cacti, with 384 basic units (BU) corresponding to the study area, consisting of eight rows of 48 plants each.

2.2 Agronomic Characteristics Evaluated

In the third production cycle, at 93 DAP, the primary cladode was used to evaluated plant height (PH - m); cladode length (CL - cm) and width (CW - cm), with graduated tape measure; cladode thickness (CT - mm), in the middle of the cladode using a digital pachymeter; number of cladodes (NC), by direct counting in the field; cladode yield (Mg ha^{-1}), expressed by the total weight of the cladodes determined on a spring balance; cladode area and cladode area index, estimated by the equations (CA = CL x CW x 0.693, cm²) and (CAI = ((CA x NC)/10,000) x 2; m²), respectively, in line with the models adopted by Padilha et al. (2016).

2.3 Statistical determination

Five plot sizes were established using different basic unit combinations, subdivided into blocks, plots, subplots, rows and plants. The plots differed in size and number of basic units, so that all of them combined filled the entire experimental area, as shown in Figure 1.

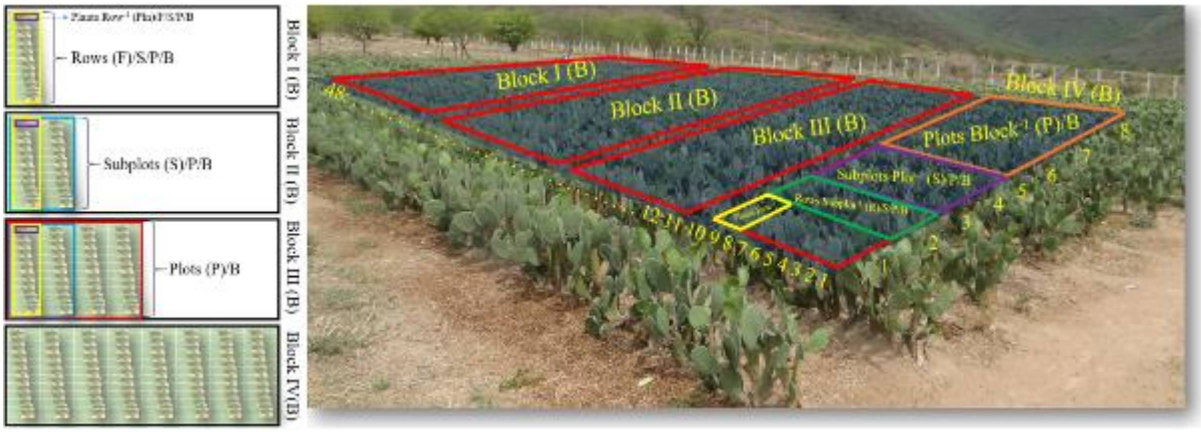

Figure 1. Schematic of the uniformity trial with 'Gigante' cactus pears, subdivided according to hierarchical classification into (B) = blocks; (P)/B = plots; (S)/P/B = subplots; (R)/S/P/B = rows; (Pln)/R/S/P/B = plants.

Optimal plot size was estimated based on comparison of variances, as proposed by Vallejo & Mendonza (1992). Statistical analyses were performed on Excel® (Donato et al., 2008), based on hierarchical classification, simulating a split-plot design in which each plant was denominated a basic unit (BU). Each descriptor was assessed considering the subdivisions of the study area (384 BU) into blocks (B), plots (P)/B, subplots (S)/P/B, rows (R)/S/P/B), and plants (Pln)/R/S/P/B (Table 1)**.**

Table 1. Subdivisions of the plots, area, number of plots, number of basic units (BU) and number of plants in the uniformity trial with 'Gigante' cactus pears

Subdivisions of the plots	Area (m^2)	Number of plots	Number of BU	Number of plants
(B)	38.4	4	96	96
(P)/B	19.2	8	48	48
(S)/P/B	9.6	16	24	24
(R)/S/P/B	4.8	32	12	12
(Pln)/R/S/P/B	0.4	384	1	1

Note. (B) = blocks; (P)/B = plots; (S)/P/B = subplots; (R)/S/P/B = rows; (Pln)/R/S/P/B = plants.

Hierarchical classification resulted in five plot sizes and their respective experimental areas, consisting of 1, 12, 24, 48 and 96 BU or 0.4; 4.8; 9.6; 19.2; 38.4 m^2. These were obtained by dividing the 384 study plants (basic units) into four blocks of 96 plants, then subdividing each block into two plots of 48 plants, each of these plots into two subplots of 24 plants, each subplot into two rows of 12 plants and, finally, one plant per row, as expressed in Table 1 and shown in Figure 1.

The original variances obtained with the hierarchical model were used to calculate reduced variances for the different plot sizes in basic units. Successive Bartlett tests were then performed to compare the homogeneity of variance (Steel & Torrie, 1980), excluding in each test the smallest plot size whose variance was significantly different.

The original estimates of variance ($\hat{V}i$) for the five plot sizes, obtained by analysis of variance, were corrected based on the smallest hierarchical classification unit (1 BU), as follows:

$$\hat{V}'_1 = \hat{V}_1;$$

$$\hat{V}'_2 = \frac{[e(d-1)\hat{V}_2 + (e-1)\hat{V}_1]}{[e(d-1) + (e-1)]};$$

$$\hat{V}'_3 = \frac{[ed(c-1)\hat{V}_3 + e(d-1)\hat{V}_2 + (e-1)\hat{V}_1]}{[ed(c-1) + e(d-1) + (e-1)]};$$

$$\hat{V}'_4 = \frac{[edc(b-1)\hat{V}_4 + ed(c-1)\hat{V}_3 + e(d-1)\hat{V}_2 + (e-1)\hat{V}_1]}{[edc(b-1) + ed(c-1) + e(d-1) + (e-1)]};$$

$$\hat{V}'_5 = \frac{[edcb(a-1)\hat{V}_5 + edc(b-1)\hat{V}_4 + ed(c-1)\hat{V}_3 + e(d-1)\hat{V}_2 + (e-1)\hat{V}_1]}{[edcb(a-1) + edc(b-1) + ed(c-1) + e(d-1) + (e-1)]};$$

where: $\hat{V}_i$ is the original variance; $\hat{V}'_i$ corrected variance; a, number of plants per row; b, number of rows per subplots; c, number of subplots per plot; d, number of plots per block, and e, the number of blocks.

The reduced variances $\hat{V}_{(xi)}$ in relation to one basic unit (plant) were calculated by dividing the corrected variances $(\hat{V}'_i)$ of the different plot sizes by their respective numbers of basic units, as shown in the equations below:

$$\hat{V}_{x=15} = \frac{\hat{V}'_3}{15}; \quad \hat{V}_{(x=5)} = \frac{\hat{V}'_4}{5}; \quad \hat{V}_{(x=1)} = \hat{V}'_5;$$

3. Results and Discussion

Variances exhibited random behavior according to the characteristic analyzed and the plot size used (Table 2). Thus, as expected, the largest assessment unit (block) or smallest basic unit (one plant) did not necessarily exhibit the smallest and lowest variances, respectively (Table 2). Furthermore, Lorentz et al. (2012) found that these parameters can be influenced by soil heterogeneity or the characteristic studied, since they are based on the coefficients of variation between adjacent plots.

Table 2. Analysis of variance as a function of the hierarchical classification criterion adopted for phenotypic descriptors in 'Gigante' cactus pears

Source of variation	DF	X (BU)	Plant height		Cladode area index		Number of cladodes		Yield	
			Vi	Vi'	Vi	Vi'	Vi	Vi'	Vi	Vi'
(B)	3	96	0.1668	0.1668	0.3535	0.3535	107.4271	107.4271	43529.7906	453.4353
(P)/B	4	48	0.0648	0.1085	0.3510	0.3521	140.7396	126.4628	16077.1647	580.0537
(S)/P/B	8	24	0.1781	0.1456	0.8210	0.6022	302.9063	220.5660	101714.9902	2801.7165
(F)/S/P/B	16	12	0.0643	0.1036	0.2237	0.4068	50.0208	132.5427	14704.1178	3343.7738
(Pln)/F/S/P/B	352	1	0.0443	0.0491	0.2638	0.2754	53.0473	59.4817	22850.7827	24248.980
Source of variation	**DF**	**X (BU)**	**Cladode area**		**Cladode length**		**Cladode thickness**		**Cladode width**	
			Vi	Vi'	Vi	Vi'	Vi	Vi'	Vi	Vi'
(B)	3	96	112.2353	112.2353	0.8079	0.8079	179.0528	179.0528	0.3483	0.3483
(P)/B	4	48	1990.2374	1185.3794	7.8764	4.8471	125.4161	148.4032	1.9749	1.2778
(S)/P/B	8	24	5888.8964	3693.9218	11.6323	8.4658	126.8962	136.9328	5.0900	3.3110
(F)/S/P/B	16	12	2895.4228	3281.7933	7.1693	7.7967	43.8829	88.9070	2.4431	2.8630
(Pln)/F/S/P/B	352	1	1631.8460	1765.3927	3.9069	4.2217	9.6705	16.0839	1.2409	1.3722

Note. Degree of freedom (DF); Plot size in basic units (X - BU) Blocks (B); Plots/Blocks (P)/B; Subplots/Plots (S)/P/B; Rows/Subplots (R)/S/P/B; Plants/Rows (Pln)/R/S/P/B; Vi' (corrected); V (reduced).

Analysis of the coefficients of variation (CV) associated with the five plot sizes demonstrated that the hierarchical increase in plot size significantly reduced the CV values of all the characteristics assessed, representing an inverse relationship between the statistical parameter (CV) and its respective plot sizes (Table 3). Similar results were reported by Vallejo & Mendonza (1992), Viana et al. (2002), Donato et al. (2008) and Henriques Neto et al. (2009) in sweet potato, cassava, banana and wheat, respectively.

Table 3. Estimated coefficients of variation (%) for the different plot sizes and characteristics of 'Gigante' cactus pears

Area (m^2)	X	Coefficient of Variation (%)							
		PH	CAI	YLD	NC	CA	CL	CT	CW

	(BU)								
0.4	1	18.82	40.13	49.92	36.58	13.63	6.91	47.63	8.05
4.8	12	7.93	14.33	19.00	15.96	5.35	2.68	19.68	3.36
9.6	24	6.66	12.25	17.42	14.50	4.02	1.98	17.30	2.55
19.2	48	4.20	6.55	7.20	7.70	1.65	1.07	12.86	1.13
38.4	96	3.62	4.65	6.06	5.05	0.50	0.30	10.06	0.46

Note. Plot size in basic units (X – BU), plant height (PH), cladode area index (CAI), yield (YLD), number of cladodes (NC), cladode area (CA), cladode length (CL), cladode thickness (CT) and cladode width (CW).

Coefficients of variation ranged between 0.30 and 49.92% as a function of the specificity of the characteristic assessed, with the highest variations related to yield and the lowest to cladodes, such as cladode area (CA), width (CW) and length (CL), with the exception of cladode thickness (CT). This is because CT is heavily dependent on the stage of vegetative growth (Silva et al., 2015) and directly related to the photosynthetic capacity and moisture content of the cladode (Scalisi et al., 2016), exhibiting high agronomic variability (Table 3).

The CV values of the plot sizes assessed were inversely proportional to plot size. These findings are similar to those reported in several studies on experimental planning, regardless of the crop analyzed or method used (Viana et al., 2002; Donato et al., 2008; Brum et al., 2016; Guarçoni et al., 2017; Cargnelutti Filho et al., 2018).

Thus, based on the aforementioned studies on plot size, it can be inferred that a rise in plot size leads to a decline in the coefficient of variation. This occurs primarily when the soil heterogeneity index (SHI) is high, as observed in the present study, where SHI was greater than 0.7 for all the characteristics analyzed except CT, which exhibited an average value of 0.45. As such, although SHI is not estimated or discussed in this study, it is important to note that under soil conditions with SHI>0.7, an increase in plot size is more effective at minimizing the influence of soil heterogeneity in the experimental area than raising the number of repetitions (Donato et al., 2018).

Based on the comparison of variances method substantiated by Bartlett's test, Table 4 indicates that the reduced variances were higher in plots with one BU, a finding inherent to the method and corroborated by other studies (Vallejo & Mendoza, 1992). Additionally, Lúcio et al. (2004), Lopes et al. (2005), Donato et al. (2008), Henriques Neto et al. (2009) and Lorentz et al. (2012) confirmed the existence of an inverse relationship between plot sizes and their respective variances, reinforcing the importance of determining the optimal plot size.

Table 4. Estimated reduced variances, in basic units (BU), for the different plot sizes and characteristics of 'Gigante' cactus pears

Area (m²)	X (BU)	Reduced variance V (x_i)							
		PH	CAI	YLD	NC	CA	CL	CT	CW
0.4	1	0.0491 a	0.2754 a	24248.9800 a	59.4817 a	1765.3927 a	4.2217 a	73.4358 a	1.3722 a
4.8	12	0.0086 b	0.0339 b	3343.7738 b	11.0452 b	273.4828 b	0.6497 b	8.5478 b	0.2386 b
9.6	24	0.0061 b	0.0251 b	2801.7165 b	9.1902 b	153.9134 b	0.3527 b	4.2037 b	0.1380 b
19.2	48	0.0023 b	0.0073 b	580.0537 b	2.6346 b	24.6954 b	0.1010 b	2.1717 b	0.0266 b
38.4	96	0.0017 b	0.0037 b	453.4353 b	1.1190 b	1.1691 c	0.0084 b	1.3908 b	0.0036 b

Note. Plot size in basic units (X – BU), plant height (PH), cladode area index (CAI), yield (YLD), number of cladodes (NC), cladode area (CA), length (CL), thickness (CT) and width (CW). The same letters exhibited no significant differences according to Bartlett's test at 5%.

This behavior was observed for all the characteristics analyzed, with specificity for CA, whereby plots consisting of 12, 24 and 48 BU displayed higher variances than the plot with one BU and lower variances than that with 96 BU, which were statistically equal. In this case, despite its high variance, the plot size consisting of 96 BU is ideal for experimental assessment of CA, but would require weighting since it exceeds the optimal size for most of the variables studied by 84 BU.

For the remaining variables, plots containing 12, 24, 48 and 96 BU were statistically equal, with lower variances than those recorded in the plot with 1 BU. As such, a plot consisting of 12 BU (4.8 m²) was considered the optimal size for experiments with 'Gigante' cactus pear because variance did not decline significantly when larger plot sizes were used (Table 4).

Additionally, in accordance with Table 4, comparison of variances can only estimate plot sizes that coincide with the sizes in basic units predefined by the model, meaning intermediate values between BU cannot be considered.

This same limitation was highlighted by Viana et al. (2002) and Donato et al. (2008) for CVM as well as the maximum curvature and modified maximum curvature methods. The comparison of variances method also exhibited limited cost effectiveness for field experiments, as observed by Guarçoni et al. (2017), who found that it restricted response plateau models.

However, when field experiments are based on accurate plot sizes, cost parameters can largely be disregarded in favor of reducing error and maximizing accuracy, unless the amounts involved are excessive (Viana et al., 2002).

The descriptors assessed here are frequently included in experiments with 'Gigante' cactus pears, making it relevant to establish an optimal plot size to analyze them accurately. Thus, since the optimal plot size for most of the characteristics was 12 BU or 4.8 m², this can be considered the most appropriate size for experiments with 'Gigante' cactus pears.

It is important to note that an optimal parcel size ensures efficient data collection in these plants, since their spines and irregular growth can make it difficult to obtain measurements in the field when plots are large, leading to potential errors. As such, this study provides researchers with the appropriate plot size for field experiments.

4. Conclusions

Plots measuring 4.8 m² with 12 basic units are the ideal size for experiments with 'Gigante' cactus pears.

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CAPÍTULO VII

REGRESSION PLATEAU FOR PLOT SIZE ESTIMATION WITH 'GIGANTE' FORAGE CACTUS PEAR

(Artigo aceito pelo periódico South African Journal of Plant and Soil)

ARTIGO 7

REGRESSION PLATEAU FOR PLOT SIZE ESTIMATION WITH 'GIGANTE' FORAGE CACTUS PEAR

Regressão com platô para estimativa do tamanho de parcelas com a palma forrageira 'Gigante'[7]

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'Gigante' cactus pear is a forage crops grown under semi-arid climates and is resilient to water-limiting conditions with a high biomass yield. The objective of this study was to estimate the optimum experimental plot size for 'Gigante' using the linear Response Plateau Model. The study was carried out at Baiano Federal Institute, campus Guanambi, state of Bahia, Brazil. An uniformity trial in which plants were subjected to the same cultural practices and spaced 2.0 m x 0.2 m was conducted. Each plant was considered as a basic unit. The Linear Response Plateau Method allowed fitting models with coefficients of determination ranging from 0.0772 to 0.881. Plot sizes ranged from 7.30 to 9.46 basic units for to the evaluated characteristic. A 10 basic unit plot size (4.0 m^2) was to be estimated using the Linear Response Plateau Regression model to be sufficient for field experiments with 'Gigante' forage cactus pear.

Index terms: agronomic characters, evaluation, *Opuntia ficus indica* Mill.

Introduction

The cactus pear (*Opuntia fícus indica* Mill) cv. Gigante is one of the best performing forage crops grown under semi-arid climates. 'Gigante' is also resilient to water-limiting conditions and has a high biomass yield. It is also an foode source with significant nutritional value (Aguiar et al. 2015). Due to these important characterirstics of 'Gigante' and its value to agriculture, studies have been conducted aimed at better understanding the management of this cultivar (Lima et al. 2016; Dantas et al. 2017; Donato et al. 2017).

[7] Artigo aceito pelo periódico South African Journal of Plant and Soil

An important aspect that wil determine the success of field experiments is defining the experimental unit. The optimum experimental plot size, in addition to improving the benefit-cost ratio of the trial (Guarçoni et al. 2017), allows for the reducing of the experimental error, ensuring experimental accuracy, and increasing reliability of inferences (Cargnelutti Filho et al. 2018).

The optimum plot size can be estimated through several methods from which the Linear Response Plateau Model (LRP) stands out for being easy to use, accurate, and providing an effective visualization of results (Paranaíba et al. 2009a, 2009b). This method estimates the optimum plot size by converting a linear model into a plateau parallel to the abscissa (the curve levels out).

The LRP model has been tested in estimating the plot size for several crops such as rice (Paranaíba et al. 2009a); wheat and cassava (Paranaíba et al. 2009b); pineapple (Leonardo et al. 2014); sugarcane (Acunha et al. 2014), forest species (Bhering et al. 2015) and castor bean (Sampaio Filho et al. 2019). These authors have indicated that this method is highly efficient in estimating the experimental plot size. Silva et al. (2012), Sousa et al. (2015) and, Guarçoni et al. (2017) also reported that the LRP model performed better than other methods evaluated for estimating the optimum plot size for radish, sunflower and cabbage, respectively.

Only a few methods have been evaluated for statistical determination of the optimum plot size for 'Gigante' forage cactus pear (Guimarães et al. 2019). Generally, field experiments with forage cactus pear are conducted using plots of different sizes based on the reseacher's experience, available resources, genetic material, among others (Queiroz et al. 2015; Padilha Junior et al. 2016; Silva et al. 2016; Donato et al. 2017).

Therefore, the aim of this study was to estimate the optimum plot size for 'Gigante' forage cactus pear using the Linear Response Plateau model.

Materials and methods

The study was conducted between 2009 and 2011 at the Baiano Federal Institute, Guanambi Campus, state of Bahia, Brazil, on a predominately flat soil classified as Litholic Neossol. The region has a tropical, hot semi-arid climate according to the Köppen classification. The mean annual rainfall and temperature during this period were 670.2 mm and 25.9 °C, respectively. The field experiment was conducted under rainfed conditions as a uniformity experiment in which no treatments were applied to plants. Tillage, fertilizer applications and all other agronomic practices were uniform throughout the experimental area and based on the recommendations for forage cactus pear (Ramalho et al., 2012). Cladodes were selected and left in the shade to cure for 15 days before planting. Organic fertilization was split into three applications with 60 t ha^{-1} $year^{-1}$ of fresh sheep manure. The first fertilizer application was in the planting furrow and the other two were side dressed at 360 and 720 days after planting (DAP).

Cladodes were planted in 10 rows with 50 cladodes per row. This results in a total experimental area of 200 m² and 500 plants, 50000 plantes ha^{-1}. One plant was considered as a basic unit (BU) with only the middle 8 rows and middle 48 plants per row used for evaluation (384 plants on 153,60 m²)

The following morphological descriptors were measured at 930 DAP: plant height - PH (m), cladode length - CL (cm) and cladode width - CW (cm), using a tape measure; cladode thickness - CT (mm), using a digital caliper in the median part of the cladode; number of cladodes - NC (unit), by direct counting of cladodes on the plant; cladode area - CA (cm²) and total cladode area - TCA (m²) were estimated by the equations: CA = CL x CW x 0.693, and TCA = ((CA x NC) / 10,000) x 2, respectively; and yield - Y (t ha^{-1}), using a field scale.

For each vegetative characteristic evaluated on an area consisting of 384 basic units, several plot sizes were combined in a way that plants could cover the whole experimental area; hence, 15 different pre-established rectangular-shaped plot sizes were evaluated (1, 2, 3……192 BU).

The LRP model, defined by a linear plateau function, is characterized by two segments: increasing or decreasing curve and a plateau response (the curve levels out), that assumes a constant value (P) (Schabenberger and Pierce 2002). The model is explained as follows:

$$CV_i=\begin{cases}\beta_0+\beta_1 X_i+\varepsilon i & \text{if}, X_i \leq X_c \\ P+\varepsilon i & \text{if}, X_i > X_c\end{cases}, \text{ i = 1,...,15} \quad (1)$$

where, CV_i is the coefficient of variation between plot sizes; X_i is the plot size in basic units; X_c is the optimum plot size in basic units; P is the coefficient of variation at the point where the curve turns into a plateau; β_0 is the intercept; β_1 is the angular coefficient; and εi is the random error associated with the CV_i (Castro et al. 2016). The optimum plot size was estimated using the equation $X_c=\frac{(\hat{P}-\hat{\beta}_0)}{\hat{\beta}_1}$, where, $\hat{\beta}_0$, $\hat{\beta}_1$ and P are parameters of Eq. 1.

Statistical analyzes were performed using the software R (R Development Core Team 2012).

Results and discussion

The coefficients of variation (CV) were estimated for the eight characteristics (Y, PH, CL, CTA, NC, CT, CA, CL and CW) under evaluation in respect to 15 plot sizes arranged on the experimental area (Table 1). CV values fluctuated across measured characteristics and plot sizes. Cladode length had the lowest CV (0.30%) while yield the highest (49.92%).

The CV indicates the variability or stability of a given characteristic; however, this coefficient may be influenced by soil characteristics and/or the size of the experimental unit (Donato et al. 2018). In this study, the CV showed a direct proportional response to the plot size, which generally occurs on heterogeneous soils; thus, smaller plots tend to detect more the variability in the environment than larger plots; hence, the smaller the plot the higher the CV (Cargnelutti Filho et al. 2018). Because of this, the CV has the greatest effect on determining the optimum size of the experimental plot (Sampaio Filho et al. 2019).

LRP model estimates the optimum plot size at the point Xc from which no significant gains in experimental precision are obtained (Schabenberger and Pierce 2002). Paranaíba et al. (2009a) and Guarçoni et al. (2017) indicated that this method is an important estimator in studies on the optimum plot size owing to its precision and adequate graphical representation of the plateau.

Peixoto et al. (2011) add that for the formation of the plateau in a segmented regression, it is necessary to use a minimum range of plot sizes for testing; in this study, we considered plot sizes of up to 192 basic units, 76,8 m². LRP method aims to establish the optimum plot size to ensure the maximum experimental precision at the lowest operating cost. Nevertheless, this method does not provide a minimum or maximum plot size as it considers only the optimum plot size (Sampaio Filho et al. 2019).

Using the LRP method for estimating the optimum plot size allowed fitting models with coefficient of determination ranging from 0.772 (Figure 1H) to 0.881 (Figure 1G). Plot sizes (Xc) estimated by this method were similar across evaluated characteristics. The smallest plot (7.30 BU) was for total cladode area (Figure 1C) and the largest plot (9.46 BU) for cladode length (Figure 1G). For these two characteristics, the CV estimates leveled off on the plateau (P) with CVs of 7.91 and 1.30%, respectively.

Generally, methods of estimating plot sizes determine sizes consisting of a number of basic units varying with the characteristic under evaluation. This is because of the genetic variability or instability of the measured characteristic, which may be further intensified by soil heterogeneity. Therefore, the CV increases in response to crop and soil variability (Donato et al. 2018; Cargnelutti Filho et al. 2018; Sampaio Filho et al. 2019; Silva et al. 2019).

Leonardo et al. (2014) reported 10 to 20 basic unit plots for pineapple; Peixoto et al. (2011) reported three to eight basic unit plots for passion fruit; and Silva et al. (2012) 1 to 21 basic unit plot sizes for radish. Sousa et al. (2015) estimated plot sizes using the LRP method, and the authors reported plot sizes ranging from 4 to 5 basic units for experimental evaluation with sunflower culture, which is more consistent with this study the ranging from 8 to 10 basic units (Figure 1).

The maximum number of basic units tested in this study was 192, 76,8 m². As indicated in Figure 1A when the CV for yield becomes constant at 9.11%, the optimum plot size has 7.58 basic units. Increasing the number of basic units does not decrease the CV, thus, there is no further increase in experimental precision.

Optimum plot sizes were 7.96; 7.30; 8.82; 8.50; 9.25; 9.46 and 9.07 basic units for plant height, total cladode area, number of cladodes, cladode thickness, area, length and width, respectively. These plot sizes are associated with the CV at the following points corresponding to the plateau formation: 4.68; 7.91; 8.05; 13.53; 2.24; 1.30 and 1.67%, respectively (Figure 1).

Guarçoni et al. (2017) using the LRP method and estimated that the optimum plot size for cabbage of 20 plants was sufficient for all characteristics normally measured. Sousa et al. (2015) reported that equally sized plots may occur in response to the agronomic similarity across the measured characteristics. However, Guarçoni et al. (2017) estimated the plot sizes using a different method, so this difference may be more attributable to the specificity of the method than the nature of the characteristics (Donato et al. 2008).

In designing an experiment the researcher usually considers all variables for evaluation; accordingly, the optimum plot size should be an average value representative of all evaluated characteristics (Acunha et al. 2014). As the main aim of this study was to determine the optimum plot size for field trials with ‘Gigante’ forage cactus pear, we selected the plot size with the highest number of basic units was selected so that all characteristics are included. Thus, experimental plots with 10 data plants are sufficiente to detect true differences between treatments.

According to Peixoto et al. (2011), the optimum plot size can be defined by averaging the estimated sizes. In this study, the average of estimated sizes is nine basic units (Figure 1); however, since all characteristics are evaluated in field trials, it is more logical to choose the plot size corresponding to the most variable characteristic so that characteristics with lower variability are included (Donato et al. 2008; Oliveira et al. 2014).

The LRP model estimated that, the optimum plot size for experimental evaluation of 'Gigante' forage cactus pear is 10 basic units. Although, Queiroz et al. (2015), Silva et al. (2016), Padilha Junior et al. (2016) and Donato et al. (2017), also working with ‘Gigante’ cactus pear used divergent, oversized plots sizes exceeding the optimum size reported herein by 30, 50, 220 and 260%, respectively. Despite these authors not presenting a benefit-cost analysis, a lower benefit-cost ratio can be inferred from the aforementioned studies.

Based on these results and considering the specificity of the ‘Gigante’ forage cactus pear, especially regarding factors hindering field measurement, such as cladode phyllotaxis and spines, it can be suggested that the maximum efficiency is obtained from experimental plots consisting of 10 basic units, estimated by the LRP regression model.

Conclusions

Results from this study using the Linear Response Plateau Regression model estimated that a 10 basic unit experimental plot size (40 m²) was sufficient for field experiments with 'Gigante' forage cactus pear and met all the evaluated characteristics.

Geographic literature

Brazil: 14°13'30" S, 42°46'5" W.

Acknowledgment

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Disclosure statement

No potential conflict of interest was reported by the authors.

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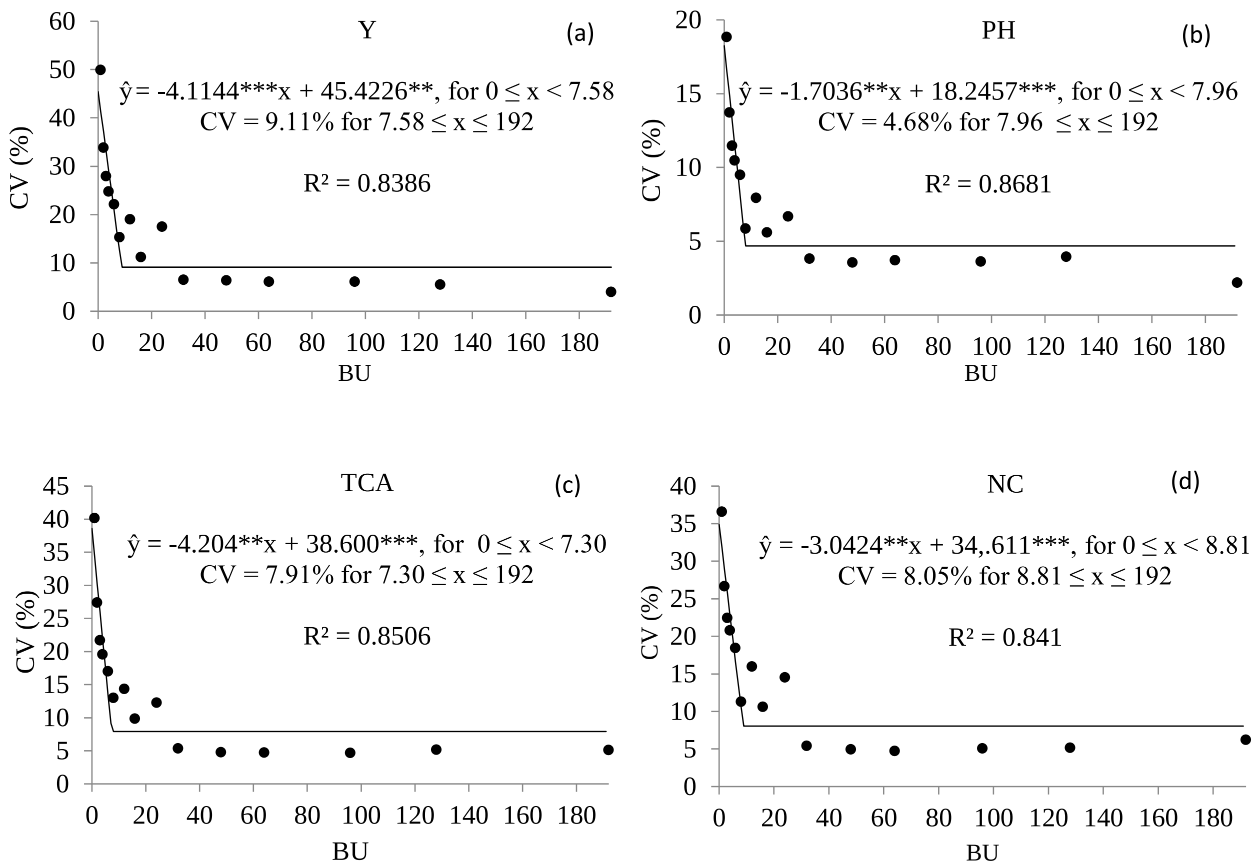
Table 1: Estimates of coefficients of variation (%) as a function of plot size in basic units (Xub) for phenotypic descriptors of 'Gigante' forage cactus pear

Xub	Y	PH	TCA	NC	CT	CA	CL	CW
1	49.92	18.82	40.13	36.58	37.01	13.63	6.91	8.05
2	33.79	13.72	27.38	26.64	29.83	9.73	5.15	5.69
3	27.95	11.47	21.66	22.44	26.37	8.17	4.33	4.83

4	24.72	10.47	19.56	20.77	25.93	7.42	3.96	4.40
6	22.12	9.49	17.00	18.43	23.97	6.72	3.46	4.04
8	15.29	5.85	12.98	11.29	14.77	4.00	2.35	2.18
12	19.00	7.93	14.33	15.96	21.43	5.35	2.68	3.36
16	11.18	5.58	9.84	10.61	16.08	3.29	1.92	1.98
24	17.43	6.66	12.25	14.50	19.60	4.02	1.98	2.55
32	6.49	3.81	5.32	5.38	12.15	1.63	1.11	0.96
48	6.36	3.54	4.75	4.94	11.74	1.39	0.77	0.90
64	6.09	3.70	4.73	4.70	11.58	1.34	0.82	0.91
96	6.06	3.62	4.65	5.04	11.13	0.50	0.30	0.46
128	5.49	3.95	5.17	5.13	12.82	0.83	0.86	0.37
192	3.93	2.18	5.12	6.21	13.16	1.84	1.28	0.68

Y = yield; PH = plant height; CTA = cladode total area; NC = number of cladodes; CT = cladode thickness; CA = cladode area; CL = cladode length; and CW = cladode width.



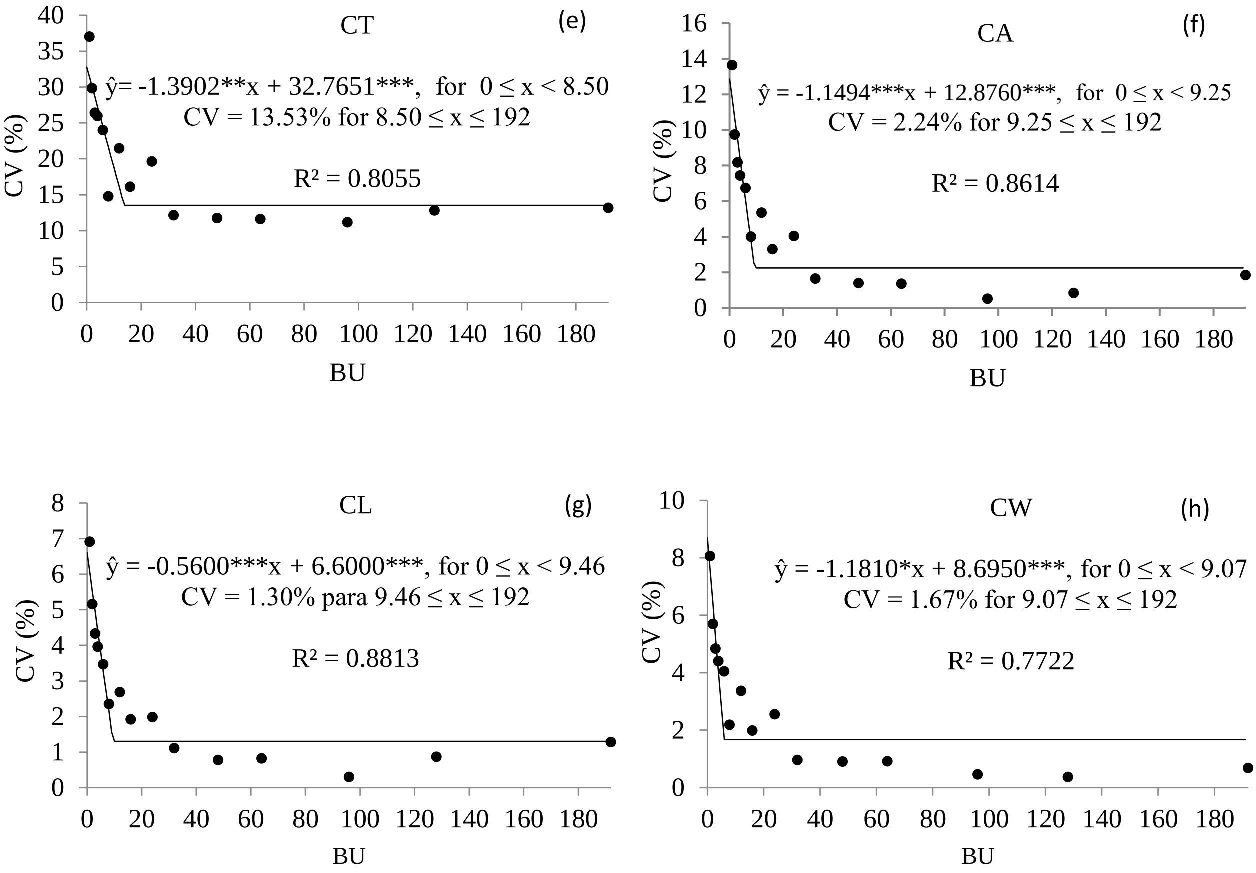


Figure 1: Linear representation of the relationship between the coefficient of variation (CV) and optimum plot size (Xc), in basic units (BU), for the characteristics: yield - Y (a), plant height - PH (b), total cladode area - TCA (c), cladodes number - NC (d), cladodes thickness - CT (e), cladodes area - CA (f), cladodes length - CC (g), and cladodes width - CW (h) in forage cactus pear. Parameter significance: 0.0001 ‘***’ 0.001 ‘**’ 0.01 ‘*’

CAPÍTULO VIII

PLOT SIZE AND SHAPE FOR FIELD TRIALS WITH FORAGE CACTUS PEAR

(Artigo aceito pela Revista Brasileira de Biometria)

ARTIGO 8

Plot size and shape for field trials with forage cactus pear[8]

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- ABSTRACT: This study aimed to determine the size and shape of experimental plots that provide maximum precision using relative information method. This trial was conducted at the Federal Institute of Bahia. Plant height, cladode length, cladode width, cladode thickness, cladode area, cladode area index, number of cladodes, cladode total area and yield were measured in the third production cycle, 930 days after planting. The plants, defined as basic units, were arranged in 39 plot sizes so that the crop would fill the whole experimental area. Then, plot shapes with higher relative information and equal plot size in basic units were selected. The experimental plot with eight basic units in size ensures higher efficiency in the experimental evaluation. This combination between size and shape, besides meeting all evaluation requirements of the characteristics normally assessed in studies with forage cactus pear, has the maximum control of soil heterogeneity, thereby decreasing experimental error and significantly increasing precision.

- KEYWORDS: Basic unit; *Opuntia ficus-indica* Mill; relative information.

Introduction

‘Gigante’ cactus pear (*Opuntia ficus-indica* Mill) is the most resilient and productive forage crop grown in semiarid regions (MARQUES *et al*., 2017); however it has the potential of attaining higher yields by using specific managements (ROCHA *et al*., 2017). Therefore, several studies have been carried out aimed at better understanding the crop, on the use of irrigation techniques, spacing, agricultural inputs, among other agronomic resources (LIMA *et al*., 2016; DANTAS *et al*., 2017; DONATO *et al*. 2017).

The success of field trials demands more precise and planned designs at a minimum cost (CARGNELUTTI FILHO *et al*., 2018; GUARÇONI *et al*., 2020). For the implications of treatments in field trials, whether testing cropping practices, fertilizer rates, hormone application, irrigation levels, or other techniques on forage cactus pear (DONATO *et al*., 2017), experimental precision is essential to improve the reliability of inferences drawn from the findings.

Obtaining significant results consistent with the proposal of the study at a minimum operational cost depends mainly on increasing experimental precision (DONATO *et al*., 2018). Thus, there are several promising methods for determining the optimum plot size in basic units, such as Modified Maximum Curvature Method - (LESSMAN and ATKINS, 1963), as verified by Guimarães *et al*. (2019a, 2019b); Comparison of Variances Method (VALLEJO and MENDONZA, 1992), studied by Guimarães *et al*. (2019b, 2019c); Linear Response Plateau Model and Quadratic Response Plateau Model (PARANAÍBA *et al*., 2009), presented by Guimarães *et al*. (2019b) and Hatheway’s Convenient Plot Size (HATHEWAY, 1961), corroborated by Guimarães *et al*. (2020).

However, due to specificities or propositions associated with the methods, determining the optimum plot size is restricted to the number of basic units, with little consideration about the shape or dimension of the experimental plot, even though an adequate plot shape is recommended as an essential foundation for the success in field trials (SOUSA *et al*., 2016).

Relative information method proposed by Keller (1949) aims to observe the effect of plot shape, based on the ratio between width and length, on experimental precision, so that the coefficients of variation of the different plot shapes having the same number of basic units are tested. Since plot dimensions are influenced by soil

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heterogeneity, climate conditions and the crop under study (SOUSA *et al*., 2016), plot shape with the lowest coefficient of variation must be selected.

Due to the need of improving studies on plot size and shape for 'Gigante' cactus pear, this study aimed to determine the plot shape that provides the maximum precision in field trials using the relative information method, as well as the number of basic units per experimental plot.

Material and methods

Experimental Characterization: Soil, Climate and Experimental Delimitation

The experiment was carried out at Baiano Federal Institute, campus Guanambi, state of Bahia, Brazil, located at 14°13′30″S, 42°46′53″W and altitude 525 m. The soil on the experimental area is a Litolic Neosol, with flat to undulating relief (EMBRAPA, 2013). The climate of the region is defined as hot, tropical semiarid, according to Köppen climate classification. Mean annual rainfall and temperature are 670.2 mm and 25.9 °C, respectively.

The experiment was conducted on a homogeneous area. Each plant was considered a basic unit – BU. Plants were subjected to the same cultural practices and spaced at 2.0 m x 0.2 m, with eight rows consisting of 48 plants each, totaling 384 BUs.

Evaluated Agronomic Characteristics

In the third production cycle, 930 days after planting, the following vegetative characteristics were measured: plant height (PH - m), cladode length (CL - cm), cladode width (CW - cm), cladode thickness (CT - mm), cladode area (CA – cm^2), cladode area index (CAI - dimensionless), number of cladodes (NC - unit), cladode total area (CTA - cm^2) and yield (Y - kg ha^{-1}).

Model for estimating relative information

Plants were arranged simulating 39 plot sizes which would allow plants to fill the whole experimental area. Then, plot shapes with higher relative information and equal plot size (BU) were selected. Relative information method (RI) evaluates the influence of plot shape as to both length and width on experimental precision. Among the 39 plot shapes arranged on the experimental area, 15 plot shapes with the highest relative information were selected (Figure 1). The coefficients of variation and the practical use of their corresponding plot shapes were assessed.

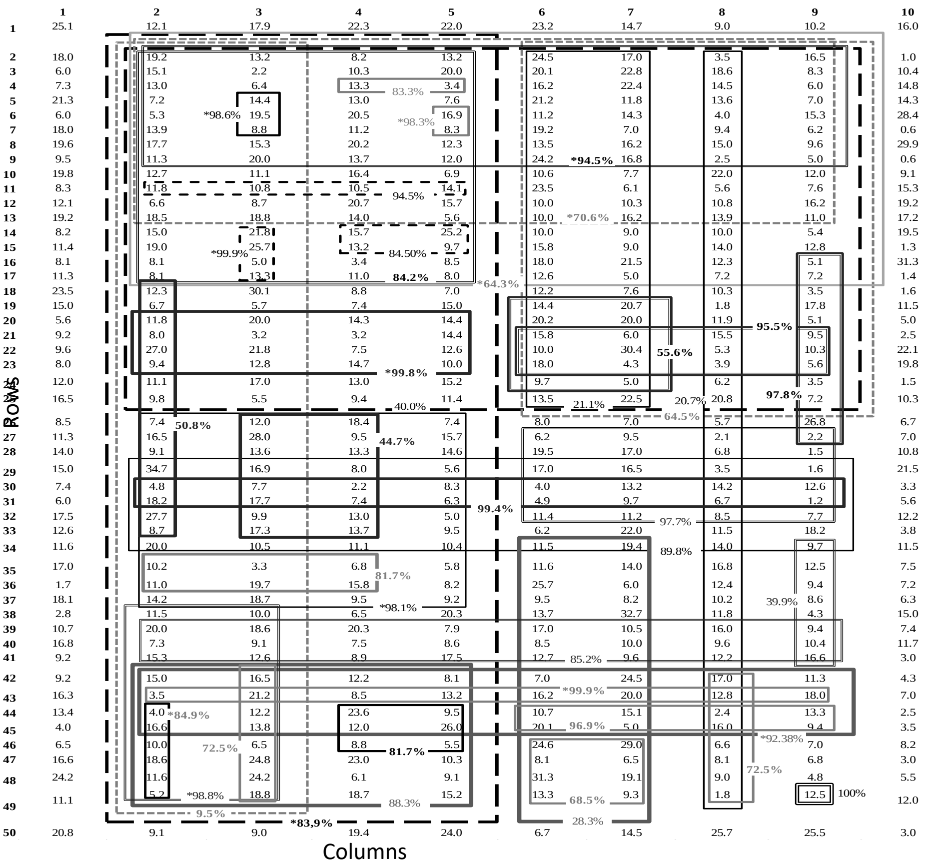


Figure 1 - Scheme of the blank trial using as example the yield of ‘Gigante’ forage cactus pear, with the 39 plot sizes derived from combining neighboring basic units.
* = Selected plot format for possible experimental combinations.

Using RI method, the between-plot variance of the phenotypic characteristics measured on plots with X BUs in size for each pre-established plot shape was determined:

$$S^2{}_x = \frac{\sum_i (X_i - M(X))^2}{NP - 1} \quad (1)$$

where Xi is the studied variable of the i-th plot,

$$M(X) = \frac{\sum_i X_i}{NP} \quad (2)$$

where M is the mean of the studied variable of plots with X BUs in size and NP is the number of plots with X BUs in size.

The relative information is a percentage measurement determined by the ratio between two variances: the variance on a plot composed by only one BU (V_1) and the comparable variance (V_c) obtained by dividing the variance by its corresponding plot size in BUs (KELLER, 1949).

$$RI(\%) = \frac{V_1}{V_c} x\,100 \quad (3)$$

By means of this equation, the variance of the plot with one BU provides 100% relative information, so the ratio between this variance and the comparable variance is the percentage of relative information of each plot shape to be selected. With this result, the most suitable plot shapes for assessing phenotypic characteristics in forage cactus pear were selected.

Owing to the specificity of the method a plot with a shape composed by one column and one row (1 C x 1 R), i.e. one BU, has the highest relative information for all variables. However, RI is not directly linked to plot size in basic units, but rather to its shape (Keller, 1949).

Soil heterogeneity indices for assessing phenotypic characteristics associated with the different plot shapes were obtained using two methods: intraclass correlation coefficient (ALVES and SERAPHIN, 2004) and the empirical relationship proposed by Smith (1938) using both a blank and designed trial.

Soil heterogeneity ($\hat{b}$) estimated by the intraclass correlation coefficient method (ALVES and SERAPHIN, 2004) can be defined by the equations:

$$\hat{b} = 1 - \frac{\log[m-(m-1)(1-\hat{p})}{\log m} \quad (4)$$

$$\hat{p} = \frac{\sigma_e^2}{\sigma_e^2 + \sigma_d^2 + \sigma_c^2 + \sigma_b^2 + \sigma_a^2} \quad (5)$$

where m is the number of units per class, (p) is the intraclass correlation coefficient, a is the number of plants on each row; b is the number of rows on each split plot; c is the number of split plots on each plot; d is the number of plots on each block; and e is the number of blocks.

The coefficient b was proposed by Smith (1938) through the linear model: LogVx = LogV1-b (Logx), where Vx is the variance of phenotypic characteristics measured in the crop for 15 selected plot sizes; V1 is the between-plot variance with one BU; and x is the plot size.

Soil heterogeneity index (b) classifies the soil variability, defined by indirect measurements of agronomic traits, into three levels: below 0.2, between 0.2 and 0.7, and above 0.7, which correspond, respectively, to the following definitions: low variability, where increasing the number of replicates is more effective than increasing plot size; medium variability, where increasing both number of replicates and plot size should be done in combination; and high variability, where increasing plot size is more effective than increasing the number of replicates. Therefore, the closer the index b is to 1 or 0, the more heterogeneous or homogeneous the experimental plot is, respectively.

In order to obtain the size and format of the plot for experimental evaluation with cactus pear, a joint analysis was established in percentage between the variation coefficient and the relative information of each selected plot size. Thus, by analyzing the graphic comparison between the aforementioned parameters, a line of connection between the points of higher and lower inflection associated with relative information and the coefficient of variation was considered, respectively.

For determining plot shapes using the relative information method, simulation routines were made on Excel® spreadsheets.

Results and discussion

Selection of plot formats by relative information

Among the 39 plot shapes distributed systematically on the experimental area (Table 1), 15 were selected with the highest relative information among the analyzed plot dimensions.

Table 1 - Plot dimensions (PD - C = number of columns and R = number of rows), number of basic units (BU), number of plots (NP) and relative information RI(%) with the various plot shapes for the variables: yield (Y), plant height (PH), total cladode area (TCA), number of cladodes (NC), cladode area index (CAI), cladode area (CA), cladode length (CL), cladode thickness (CT) and cladode width (CW) for the experimental evaluation of 'Gigante' cactus pear.

PD (C x R)	BU	NP	Area (m^2)	Relative information RI (%)									C
				Y	PH	TCA	NC	CAI	CA	CL	CT	CW	
4 x 48	192	2	76.80	83.92	38.97	44.87	34.35	48.07	28.72	15.13	4.12	72.89	S
8 x 24	192	2	76.80	40.02	10.37	45.74	33.96	45.74	28.22	13.34	3.60	63.57	NS
8 x 16	128	3	51.20	64.52	17.75	47.01	39.77	47.01	93.90	49.97	4.96	75.23	S
2 x 48	96	4	38.40	9.52	16.65	14.08	7.39	14.08	15.30	20.01	3.81	13.03	NS
4 x 24	96	4	38.40	64.49	23.91	45.73	26.37	45.73	65.15	41.65	5.10	78.26	NS
8 x 12	96	4	38.40	70.60	28.08	77.50	54.78	77.50	94.76	54.40	8.67	97.26	S
4 x 16	64	6	25.60	84.23	34.23	55.07	35.71	55.07	74.51	42.14	7.11	75.94	NS
8 x 8	64	6	25.60	94.48	40.35	99.10	94.46	95.72	80.54	89.00	11.99	97.68	S
1 x 48	48	8	19.20	20.66	22.56	27.48	16.18	27.48	26.36	26.48	7.28	20.84	NS
2 x 24	48	8	19.20	21.07	19.48	25.70	14.67	25.70	26.50	26.69	5.96	24.76	NS
8 x 6	48	8	19.20	89.76	58.96	96.53	34.34	59.40	89.79	84.05	14.64	84.27	NS
4 x 12	48	8	19.20	98.05	59.41	78.22	47.03	78.22	99.44	86.96	15.89	96.17	S
2 x 16	32	12	12.80	28.25	26.66	35.87	20.88	35.87	35.37	33.97	8.78	33.79	NS
4 x 8	32	12	12.80	88.30	52.75	95.89	66.63	95.89	98.00	74.45	14.80	84.99	NS
8 x 4	32	12	12.80	92.38	76.32	97.63	86.59	97.63	98.45	96.99	22.57	88.34	S
4 x 6	24	16	9.60	97.36	51.12	98.13	70.01	98.13	86.32	74.90	17.75	84.40	NS
1 x 8	24	16	9.60	39.96	29.86	42.97	27.09	42.97	33.73	32.80	9.97	30.02	NS
8 x 3	24	16	9.60	85.24	91.75	84.34	68.79	97.31	83.13	92.80	29.68	94.61	NS
2 x 12	24	16	9.60	98.80	99.90	88.91	79.61	98.29	90.84	99.59	35.12	99.54	S
1 x 16	16	24	6.40	50.79	39.18	59.38	38.83	59.38	50.35	43.97	14.01	47.11	NS
2 x 8	16	24	6.40	44.73	44.01	63.13	38.52	63.13	58.89	56.25	16.28	54.65	NS
4 x 4	16	24	6.40	99.76	92.24	93.53	74.36	93.53	96.85	81.29	53.40	98.27	S
8 x 2	16	24	6.40	99.34	91.14	89.68	73.92	89.68	94.25	77.27	42.62	95.46	NS
2 x 6	12	32	4.80	55.64	48.57	68.17	43.87	68.17	61.93	61.17	20.36	58.09	NS
4 x 3	12	32	4.80	95.47	79.31	82.40	92.34	82.40	86.73	88.67	34.52	76.03	NS
1 x 12	12	32	4.80	97.83	89.25	91.50	99.82	91.50	91.88	93.87	36.19	81.19	S
1 x 8	8	48	3.20	72.47	59.67	92.15	62.51	92.15	74.34	68.73	24.49	68.17	NS
2 x 4	8	48	3.20	68.53	63.71	76.83	54.56	76.83	70.47	65.17	29.69	70.70	NS
4 x 2	8	48	3.20	96.87	83.52	91.71	86.02	91.71	94.63	98.83	49.01	96.42	NS
8 x 1	8	48	3.20	99.94	96.84	95.55	98.44	97.94	98.51	99.80	77.24	97.36	S

Columns

1 x 6	6	64	2.40	84.87	78.64	97.48	65.67	99.34	89.30	79.73	39.16	92.62	S
2 x 3	6	64	2.40	81.68	72.99	89.87	70.37	97.86	87.32	78.24	38.46	85.34	NS
1 x 4	4	96	1.60	99.89	96.88	94.68	99.28	99.94	99.54	98.68	93.35	96.28	S
2 x 2	4	96	1.60	84.50	82.17	90.08	73.23	90.08	92.15	85.27	52.16	94.85	NS
4 x 1	4	96	1.60	94.50	91.52	84.80	85.88	84.80	98.81	91.82	86.93	91.64	NS
1 x 3	3	128	1.20	98.60	89.70	97.23	88.62	97.23	92.84	84.96	53.71	92.60	S
1 x 2	2	192	0.80	98.25	99.70	96.68	94.29	96.68	98.13	99.04	97.71	95.04	S
2 x 1	2	192	0.80	83.27	98.66	83.14	80.19	83.14	92.45	91.77	84.54	93.51	NS
1 x 1	1	384	0.40	100	100	100	100	100	100	100	100	100	S

Criterion (C), non-selected (NS) and selected (S) plot shape.

The different rectangular shaped plots such as 4 C x 48 R and 8 C x 24 R have the same size in terms of basic units, 192 BUs, and yet relative information diverges, with 83.92% for the former and 40.02% for the latter, for yield (Table 1). This comparison between shapes allows inferring that a plot with higher RI controls more efficiently the variability in field trials and should be recommended due to the smaller experimental error, and hence, higher precision. For all combinations between columns and rows where it is possible for the crop to fill the whole experimental area, the most suitable shape was determined by the analysis or comparison of RI (KELLER, 1949).

Most plot sizes have different shape options by combining the number of columns and rows (Table 1). Conversely, the increase in plot size (BU), regardless of its shape, tends to have lower relative information values (Table 1). This was expected since by this method, a plot with only one BU has 100% relative information (KELLER, 1949).

The comparison of variability indices, coefficient of variation and comparable variance, to the relative information using experimental plots of equal size reveals the influence of plot shape on experimental precision (SOUSA *et al*., 2016). Nonetheless, relative information has a greater effect on the selection of large plots, while for a reduced plot size, plot shape has less control of the experimental error (OLIVEIRA *et al*., 2011).

Although relative information also uses the comparable variance in defining the best plot shape, this method is more commonly used for being more practical as it indicates, in terms of percentage, the most appropriate plot shape (Table 1). Plot shape is selected based on the greater value of the relative information of a given experimental area, which mainly occurs in response to soil heterogeneity. Petersen (1994) adds that plot shape is more important in heterogeneous environments or with high gradient of variability, as observed in this study on forage cactus pear.

Soil heterogeneity index

Values of b estimated by the method of Smith (1938) using data from a blank trial as well as a trial simulating a split plot design, and by the intraclass correlation coefficient developed by Alves and Seraphin (2004) (Figure 2). Soil variability estimates ranged from 0.402 to 1.419 across characteristics, which means that the soil is heterogeneous or with low correlation between neighboring basic units (SMITH,1938).

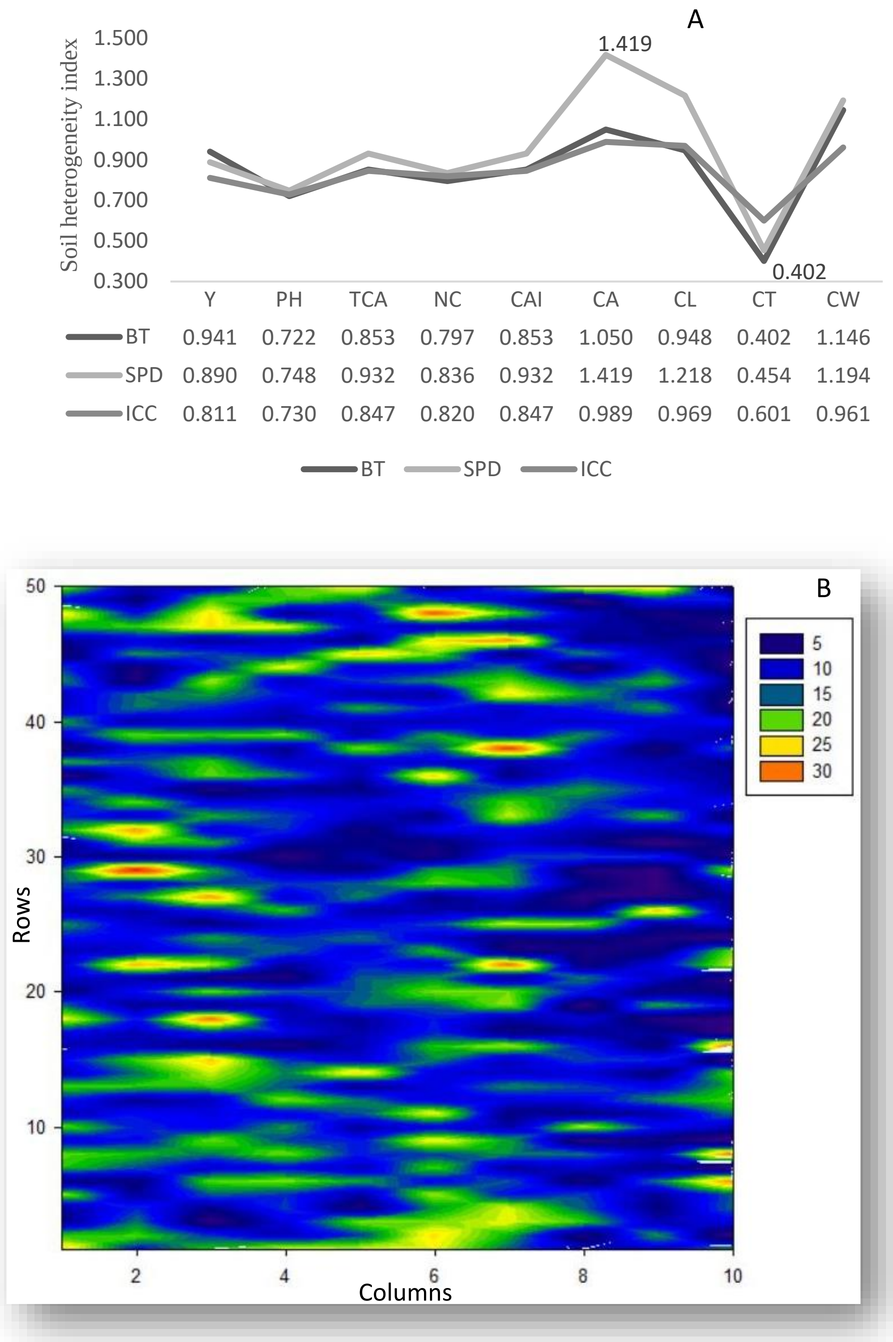


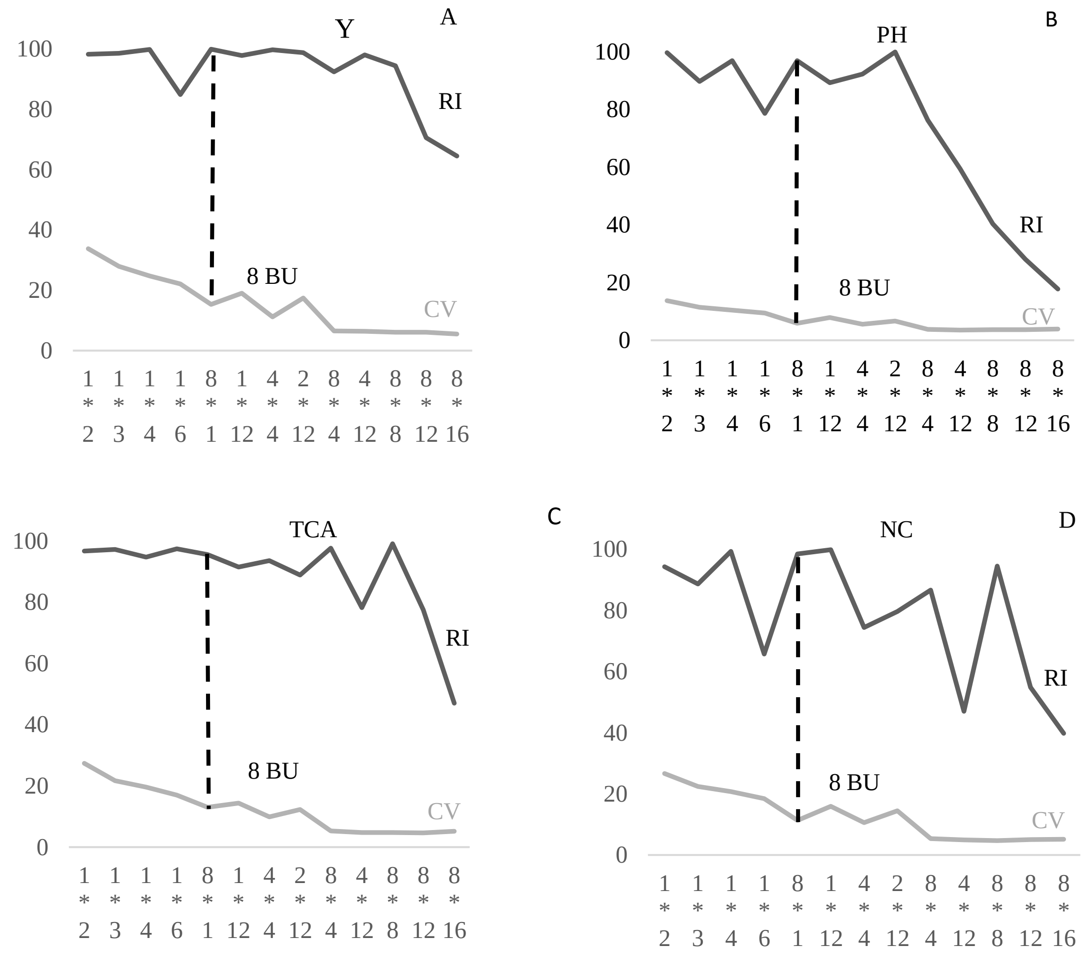
Figure 2 - Values of soil heterogeneity index (b) estimated by the method proposed by Smith (1938) on the basis of a blank trial (BT) and a trial designed as a split plot design (SPD), and by the intraclass correlation coefficient (ICC) (LIN and BINNS, 1984), for the variables: yield (Y), plant height (PH), total cladode area (TCA), number of cladodes (NC), cladode area index (CAI), cladode area (CA), cladode length (CL), cladode thickness (CT) and cladode width (CW) for the experimental evaluation of 'Gigante' cactus pear (A). Surface representation of the productivity response (Kg ha^{-1}) obtained in each plant as a function of its positioning within the experimental area, in which the shades in blue and orange/yellow indicate, respectively, low and high productivity (B).

Furthermore, based on Figure 2, coefficient b is highly similar across estimated values for each measured characteristic, with the lowest variation between the methods being 0.03, 0.04, 0.08, 0.08 and 0.13 for plant height, number of cladodes, total cladode area, cladode area index and yield, respectively. However, the variables directly related to cladode size had the highest variation: 0.43, 0.27, 0.23 and 0.20 for cladode area, length, width and thickness, respectively.

The high variability in productivity can be seen in Figure 2B. This Figure shows places within the experiment where the plants showed low productivity (Dark blue color) and other places where the plants showed higher productivity (Yellow and orange colors). This variability was irregular, as no distribution gradient was observed in the direction of the rows or columns. The variability in the productivity of forage cactus pear within the experiment can be justified by different factors, such as the soil heterogeneity index (Figure 2A) (SMITH, 1938), organic fertilization and spacing (PADILHA JUNIOR *et al*., 2016; DONATO *et al*., 2017; BRITO *et al*., 2018), irrigation (DANTAS *et al*., 2017), cultivation systems and harvest management (AMORIM *et al*., 2017).

Relation between relative information and coefficient of variation

The analysis of coefficient b on the experimental area shows high between-plot heterogeneity for all characteristics. This suggests that increasing plot size is more effective than increasing the number of replicates. Additionally, the graphical comparison between the coefficient of variation and the relative information may be useful in selecting the most suitable plot size and shape for field trials on forage cactus (Figure 3).



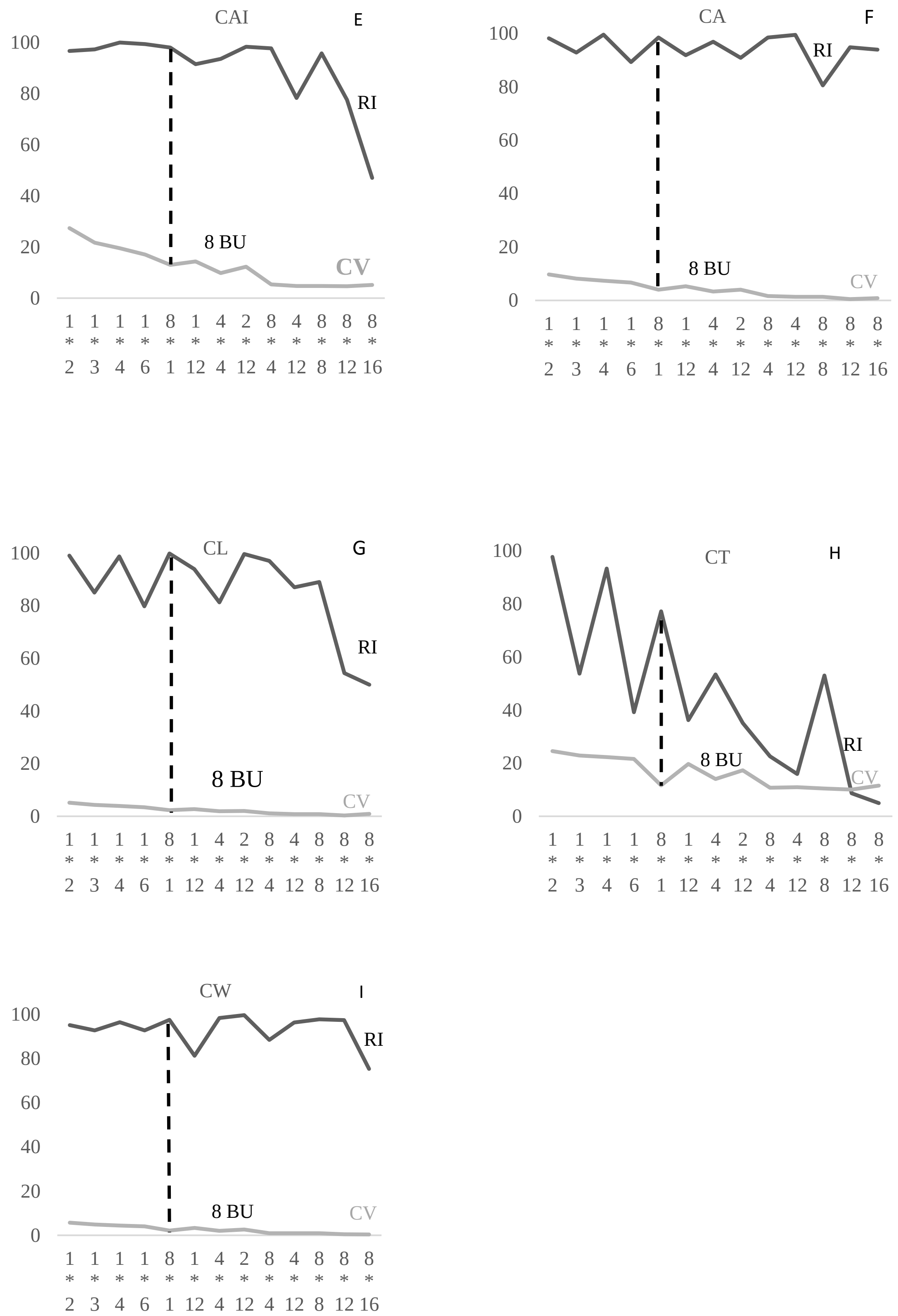


Figure 3 - Graphical comparison between the coefficient of variation and relative information for plot sizes and shapes for field trials on forage cactus with the following characteristics: yield - Y (A), plant height - PH (B), total cladode area - (TCA - C), number of cladodes - NC (D), cladode area index - CAI (E), cladode area - CA (F), cladode length - CL (G), cladode thickness - CT (H) and cladode width - CW - I). BU – basic units.

Among the 39 sizes and shapes of pre-established plots (Figure 1, Table 1 and Figure 3) the experimental arrangements having higher relative information were selected for all measured characteristics (Figure 1). 15 plot sizes and shapes with both higher relative information (RI) and stable coefficient of variation (CV) were evaluated. Based on the association of these two parameters, it was possible to graphically define the optimum plot size and shape for field trials on ‘Gigante’ forage cactus pear (Figure 3).

In the graphical analysis between the variability indices determined in this study, RI and CV, and plot shapes (C * R), the optimum plot sizes were consistent with eight BUs and 8 C x 1 R shape for all characteristics (Figure 3), representing an area of 3.2 m². The comparison of 8 C x 1 R shape to other experimental plot shapes, such as the combinations 8 C x 4 R, 1 C x 4 R and 1 C x 6 R, shows that the latter shapes are inferior to the former with respect to the inflection point between the highest RI and the lowest CV (Figure 3).

Thus, a plot size of eight BUs and 8 C x 1 R shape ensures higher efficiency in the experimental evaluation since this combination between size and shape has a better control of soil heterogeneity, thereby reducing experimental error and significantly increasing precision. It is worth noting that the size of the experimental plot recommended in this study are in agreement with the findings reported by Guimarães *et al*. (2019a).

Moreover, higher CV values were associated with plots with only one BU (1 C x 1 R), which is understandable seeing that plots of this size are more affected by soil variability (Figure 2). For plot sizes and shapes selected in this study, CV values ranged from 17 to 1.39% for cladode area index (Figure 3E) and cladode area (Figure 3F), respectively. For these same characteristics, CAI and CA, RI values were 99.34 and 98.51%, respectively. These results are highly similar, especially for the CV and RI values, in estimating plots sizes and shapes for sunflower (SOUSA *et al*., 2016).

Size and shape of experimental plots have been discussed by several papers. Sousa *et al*. (2016), Donato *et al*. (2018), Guimarães *et al*. (2019a, 2019b), Sampaio Filho *et al*. (2019) and Silva *et al*. (2019) reported a reduction in CV with increasing plot size. However, after determining the optimum plot size, no significant increase in precision has been reported with increasing plot size (CARGNELLUTI FILHO *et al*., 2018).

Other studies show that RI decreases in response to the increase in plot size (LÚCIO *et al*., 2010; SOUSA *et al*., 2016). Keller (1949) discusses that the ideal plot size is the one from which RI values become stable. Furthermore, according to the creator of the method, the RI of the plot tends to increase as the plot size decreases, which favors the recommendation of plots with values close to one BU. Thus, it can be inferred from the lower CV and the higher RI values that the size of the plot with eight BUs and 8 C x 1 R shape provides the best conditions for field trials on 'Gigante' cactus pear.

Studies on 'Gigante' cactus pear have been carried out with several plot sizes measuring 15 (QUEIROZ *et al*., 2015), 32 (SILVA *et al*., 2016), 36 (PADILHA JUNIOR *et al*., 2016) and 32 basic units (BRITO *et al*., 2018). Nevertheless, based on the findings reported herein, the experimental area can be optimized with a significant reduction in the size and shape of the plot, with further gains in experimental precision by minimizing error and number of sampling units. Thus, plots with eight BUs showed satisfactory results for experimental evaluation with 'Gigante' cactus pear.

Conclusions

Plot size with eight basic units and rectangular shape 8 $_C$ x 1 $_R$, representing an area of 3.2 m^2, is considered the most suitable experimental plot for evaluating 'Gigante' cactus pear.

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- *RESUMO: Este estudo teve como objetivo determinar o tamanho e a forma das parcelas experimentais que fornecem máxima precisão usando o método da informação relativa. O ensaio foi realizado no Instituto Federal Baiano. A altura da planta, o comprimento do cladódio, a largura do cladódio, a espessura do cladódio, a área do cladódio, o índice da área do cladódio, o número de cladódios, a área total do cladódios e o rendimento foram avaliados no terceiro ciclo de produção, 930 dias após o plantio. As plantas, definidas como unidades básicas, foram dispostas em 39 formatos de parcelas, capazes de ocupar toda a área experimental. Em seguida, as formas das parcelas foram selecionadas com informações relativas mais altas e tamanhos iguais de parcelas em unidades básicas. O arranjo experimental com oito unidades de tamanho básico assegura maior eficiência na avaliação experimental. Essa combinação de tamanho e forma, além de atender a todos os requisitos para avaliar as características normalmente avaliadas em estudos com a palma forrageira, apresenta controle máximo da heterogeneidade do solo, diminuindo o erro experimental e aumentando significativamente a precisão.*

- *PALAVRAS-CHAVE: Unidades básicas; Opuntia ficus-indica* Mill*; informação relativa.*

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CAPÍTULO IX

METHODS FOR ESTIMATING OPTIMUM PLOT SIZE FOR ‘GIGANTE’ CACTUS PEAR

(Artigo publicado pelo Journal of Agricultural Science)

ARTIGO 9

Methods for Estimating Optimum Plot Size for 'Gigante' Cactus Pear[9]

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Abstract

The optimum plot size for 'Gigante' cactus pear can be estimated by several methods; thus, ultimately aiming for efficiency, simple use and high precision, the objective of this study was to compare methods for estimating plot sizes: modified maximum curvature method, Hatheway's convenient plot size method, linear and quadratic response plateau models, and comparison of variances method for evaluating phenotypic characteristics in experiments with 'Gigante' cactus pear. Plot sizes were estimated by conducting a uniformity trial. Estimated optimum plot sizes varied with the method and vegetative characteristic. The quadratic response plateau regression estimated the largest plot sizes, whereas Hatheway's method estimated the smallest plot sizes. Comparison of variances method estimated intermediate plot sizes in comparison with the other methods for most measured characteristics. Plots sizes estimated by modified maximum curvature method are more consistent with results reported by studies on 'Gigante' cactus pear. 10 basic unit plot sizes estimated by the linear response plateau model can be used with high precision and practical feasibility for growing cactus pear, thereby improving the use of resources.

Keywords: experimental model, experimental precision, *Opuntia ficus-indica* Mill

1. Introduction

Although 'Gigante' cactus pear (*Opuntia ficus-indica* Mill) is considered the forage crop with the highest productivity, yields recorded in Brazil do not reach satisfactory levels (Marques et al., 2017). Thus, due to factors limiting the cultivation of this crop, several studies have been carried out aimed at providing alternatives that favor its sustainable development, associating highest performance with food security (Lima et al., 2016; Donato et al., 2017; Dantas et al., 2017).

Field trials with 'Gigante' cactus pear are conducted in several Brazilian regions with the objective of improving production, decreasing costs and increasing efficiency of agricultural inputs, thereby providing minimum conditions for feasible farming (Dantas et al., 2017). Successful investigations consist of observing statistical differences between treatments. Accordingly, finding out the suitable size and shape of the experimental plot is necessary to lessen the experimental error (Cargnelutti Filho et al., 2018).

The plot size should not be determined indiscriminately. The estimation of the plot size must take into account site-specific soil and climate conditions under which the crop is grown since the optimum plot size varies with the heterogeneity of the experimental area (Donato et al., 2018). Therefore, plot size has a direct impact on the precision and quality of the experimental data (Cargnelutti Filho et al., 2014; Schmildt et al., 2016; Lavezo et al.,

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2017). The optimum plot size for 'Gigante' cactus pear can be estimated by several procedures; however, a few methods stand out owing to their efficiency, simplicity and high accuracy: modified maximum curvature method (Lessman & Atkins, 1963), Hatheway's convenient plot size method (Hatheway, 1961), linear and quadratic response plateau models (Paranaíba et al., 2009), and comparison of variances method (Vallejo & Mendonza, 1992).

Therefore, the objective of this study was to compare methods for estimating plot sizes for evaluation of phenotypic characteristics of 'Gigante' forage cactus pear. The methods are: modified maximum curvature, Hatheway's method, linear response plateau, quadratic response plateau, and comparison of variances method.

2. Material and Methods

2.1 Experimental Characterization: Soil, Climate and Experimental Delimitation

The experiment was carried out at Federal Institute Baiano, campus Guanambi, Bahia state, Brazil, located at 14°13′30″S, 42°46′53″W and altitude 525 m. The soil on the experimental area is a Litolic Neosol, with flat to undulating relief (EMBRAPA, 2013). Evaluations began 930 days after planting. Over the evaluation period, annual mean rainfall and temperature were 670.2 mm and 25.9°C, respectively (CODEVASF, 2018).

Based on the uniformity trial, agronomic practices such as tillage, liming and fertilization, were performed uniformly throughout the experimental area, following the recommendations for the crop (Ramalho et al., 2012). Each plant was considered a basic unit, planted at a spacing 2.0×0.2 m (25,000 plants ha^{-1}). The whole experimental area consisted of 10 rows with 50 plants on each row. The outer plant rows and the first and last plant of each row were not considered for evaluation (border rows), so that only the eight central rows with 48 plants each were evaluated, that is, 384 basic units.

Cladodes used for establishing the experimental area were collected on the middle third of 600-day-old 'Gigante' cactus pear plants growing on an unharvested field. After selecting the cladodes, they remained in shade for 15 days to cure. Afterwards, the cladodes were planted facing the east-west direction, with half cladode buried in the soil.

2.2 Evaluated Agronomic Characteristics

Vegetative characteristics and how they were measured were: plant height (PH-m), cladode length (CL-cm) and cladode width (CW-cm), determined with a measuring tape; cladode thickness (CT-mm), determined with a digital caliper rule; number of cladodes (NC-unit), determined by counting; cladode area (CA-cm^2), estimated by the equation CA = CL × CW × 0.693; and total cladode area (TCA-cm^2), product of CA and NC. These procedures are commonly used in the literature for cactus pear (Donato et al., 2017). Lastly, yield (Mg ha^{-1}) was determined with a weighing scale over the third production cycle.

To size plots, we used combinations between rows and columns that would allow plants to cover the total area within plots on the experimental area. As the coefficient of variation (CV) indicates the optimum plot size, it was calculated, so that 15 different plot shapes were used (Table 1).

Table 1. Arrangement of columns and rows and their respective sizes, corresponding number of plots, basic units composing these plots and area for 'Gigante' cactus pear

Columns	Rows	Plot size		Number of plots	Basic unit	Area
		Width	Length			
4	48	8	9.6	2	192	76.80
8	16	16	3.2	3	128	51.20
8	12	16	2.4	4	96	38.40
8	8	16	1.6	6	64	25.60
4	12	8	2.4	8	48	19.20
8	4	16	0.8	12	32	12.80
2	12	4	2.4	16	24	9.60
4	4	8	0.8	24	16	6.40
1	12	2	2.4	32	12	4.80
8	1	16	0.2	48	8	3.20
1	6	2	1.2	64	6	2.40
1	4	2	0.8	96	4	1.60

1	3	2	0.6	128	3	1.20
1	2	2	0.4	192	2	0.80
1	1	2	0.2	384	1	0.4

Note. Width (m), length (m), area (m^2).

2.3 Models for Estimation of Experimental Plot Size

The modified maximum curvature method associates through a power regression equation the coefficients of variation between plots with their respective sizes (Facco et al., 2018). Using Hatheway's method, convenient plot sizes are estimated through a combination matrix (Sousa et al., 2016). Linear and quadratic response plateau models estimate the optimum plot size by converting a linear or quadratic model, respectively, into a plateau (Guarçoni et al., 2017). Comparison of variances method establishes a hierarchical classification criterion, and after obtaining variances and reduced variances, a test for homogeneity of variance is conducted to define the best plot size (Henriques Neto et al., 2009).

The modified maximum curvature method represented by the power function $Y = a/x^b$, determines algebraically the optimum plot size by relating the coefficient of variation to the plot size in basic units (Lessman & Atkins, 1963).The maximum curvature point is determined by the equation:

$$X_{mc} = \left[\frac{\widehat{A}^2\widehat{B}^2(2\widehat{B}+1)}{\widehat{B}+2}\right]^{\frac{1}{(2+2B)}} \quad (1)$$

where, X_{mc} is the optimum plot size, $\widehat{A}$ and $\widehat{B}$ are the respective estimates of coefficients A and B of the power function. This formula was obtained by Meier and Lessman (1971).

To determine the convenient plot size (Hatheway, 1961), the following model was used:

$$X^b = \frac{2(t_1 + t_2)^2 CV^2}{rd^2} \quad (2)$$

where, X is the plot size in basic units; CV is the coefficient of variation of plots consisting of one basic unit; b is the index of soil heterogeneity (Smith, 1938), represented by the linear equation: $\log V_x = \log V_1 - b(\log x)$, where V_x is the variance between vegetative characteristics for each corresponding plot size, $V_1$is the variance between plots with one basic unit, and *x* is the plot size in basic units; t_1 is the critical value of Student's t distribution at the significance level of $\alpha 1$; t_2 is the critical value of Student's t distribution at significance level $\alpha 2 = 2(1 - P)$ where P is the probability of obtaining a significant result (0.80); r is the number of replications; and d is the true difference between two treatments as a percentage of the mean.

Furthermore, concerning Hatheway's method (1961), it is worth considering that t_1 and t_2 values fluctuate as to the residual degree of freedom and, consequently, as to the number of treatments and blocks. In this case, we adopted five treatments and four replications to estimate plot sizes. Values for d were set based on the CV of evaluated characteristics.

The linear response plateau model (Paranaíba et al., 2009) was defined as:

$$CV_i = \begin{cases} \beta X_0 + \beta_1 X_i + \varepsilon_i & \text{if, } X_i \leq X_c \\ P + \varepsilon_i & \text{if, } X_i > X_c \end{cases}, \; i = 1, \ldots 15 \quad (3)$$

where, CV_i is the coefficient of variation between plot sizes X_i; X_i is the plot size in basic units; X_c is the optimum plot size in basic units; P is the coefficient of variation on the plateau; $\beta_0$is the intercept;$\beta_1$is the angular coefficient; and εi is the random error associated with CV_i (Castro et al., 2016). The ratio between the optimum plot size and plateau formation was determined. The optimum plot size was calculated by the equation $X_c = (\widehat{P} - \widehat{\beta}_0)/\widehat{\beta}_1$, where,$\widehat{\beta}_0$,$\widehat{\beta}_1$ and P are parameters of the linear response plateau model.

The quadratic response plateau model estimates the optimum plot size by converting a quadratic function into a plateau, as follows:

$$CV_i = \begin{cases} \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \varepsilon_i & \text{if, } X_i \leq X_c \\ P + \varepsilon_i & \text{if, } X_i > X_c \end{cases}, \; i = 1, \ldots 15 \quad (4)$$

where, β_0, β_1 and β_2 are estimated parameters of the quadratic function. If $X_i \leq X_c$, a quadratic model is produced with the CV_i values; If $X_i > X_c$, the equation establishes a plateau (Rezende et al., 2007). The first derivative of the quadratic equation is the optimum point:

$$X_c = -\frac{\beta_1}{2\beta_2} \quad (5)$$

where, X_c represents the plateau formation on the quadratic response plateau model:

$$P=\beta_0-\frac{\beta_1^2}{4\beta_2} \quad (6)$$

Through the comparison of variances method, variances are reduced to one basic unit, and then, the variance of each plot is divided by the corresponding number of basic units. Comparisons of consecutive Bartlett's tests are performed for each possible pair of plot size aiming to identify the homogeneity of variance (Steel &Torrie, 1980). After that, the smallest plot with a statistically different variance was excluded in each test. Finally, based on the homogeneity of variances within a group of plots, the plot composed by the lowest number of basic units was selected.

The original variances ($\hat{V}_i$) of five plots sized in the field, 96, 48, 24, 12 and 1, were corrected in relation to the lowest number of basic units (one), as follows:

$$\hat{V}'_1=\hat{V}_1;$$

$$\hat{V}'_2=\frac{[e(d-1)\hat{V}_2+(e-1)\hat{V}_1]}{[e(d-1)+(e-1)]};$$

$$\hat{V}'_3=\frac{[ed(c-1)\hat{V}_3+e(d-1)\hat{V}_2+(e-1)\hat{V}_1]}{[ed(c-1)+e(d-1)+(e-1)]};$$

$$\hat{V}'_4=\frac{[edc(b-1)\hat{V}_4+ed(c-1)\hat{V}_3+e(d-1)\hat{V}_2+(e-1)\hat{V}_1]}{[edc(b-1)+ed(c-1)+e(d-1)+(e-1)]};$$

$$\hat{V}'_5=\frac{[edcb(a-1)\hat{V}_5+edc(b-1)\hat{V}_4+ed(c-1)\hat{V}_3+e(d-1)\hat{V}_2+(e-1)\hat{V}_1]}{[edcb(a-1)+edc(b-1)+ed(c-1)+e(d-1)+(e-1)]} \quad (7)$$

where, $\hat{V}_i$ is the original variance; $\hat{V}'_i$ is the corrected variance; a is the number of plants on each row; b is the number of rows per split-plot; c is the number of split-plots per plot; d is the number of plots per block; and e is the number of blocks.

The reduced variances $\hat{V}_{(xi)}$ in relation to one basic unit were estimated by dividing the corrected variances ($\hat{V}'_i$) of several plot sizes by their respective number of basic units, as in the following equations:

$$\hat{V}_{x=i}=\frac{S'^2_{xi}}{x_i};\ \hat{V}_{(x=180)}=\frac{\hat{V}'_1}{180};\ \hat{V}_{(x=45)}=\frac{\hat{V}'_2}{45};$$

$$\hat{V}_{x=15}=\frac{\hat{V}'_3}{15};\ \hat{V}_{(x=5)}=\frac{\hat{V}'_4}{5};\ \hat{V}_{(x=1)}=\hat{V}'_5 \quad (8)$$

2.4 Statistical Analysis

Statistical procedures were carried out on Excel® spreadsheets (Donato et al., 2008, 2018) and using the software R (R Development Core Team, 2012).

3. Results and Discussion

Based on the soil heterogeneity coefficient (b), the experimental area was classified as heterogeneous, with regression coefficients higher than 0.7 for all evaluated traits. These experimental conditions indicate that increasing plot size is more effective than increasing the number of replicates when aiming at higher experimental precision (Hou et al., 2015). However, once the optimum plot size is determined, further increases in precision may be obtained by using more replicates (Souza et al., 2018).

Optimum plot sizes for 'Gigante' cactus pear were determined using the methods modified maximum curvature, Hatheway's convenient plot size, linear response plateau, quadratic response plateau and comparison of variances method. With the modified maximum curvature method, the optimum plot size for yield contained eight basic units or 3.2 m^2. As for the following vegetative characteristics: plant height, cladode area, total cladode area, cladode length, cladode width, cladode thickness, and number of cladodes, the optimum plot sizes were four (1.6 m^2), four (1.6 m^2), seven (2.8 m^2), three (1.2 m^2), three (1.2 m^2), four (1.6 m^2) and six (2.4 m^2) basic units (plants) per plot, respectively (Table 2).

Table 2. Number of basic units composing the optimum plot sizes for 'Gigante' forage cactus pear estimated by the modified maximum curvature method (MMC), convenient plot size (CPS), linear response plateau model (LRP), quadratic response plateau model (QRP) and comparison of variances method (CVM). Coefficient of variation associated to plot sizes (CV), Optimum plot size (OPS)

Trait	MMC	CPS	LRP	QRP	CVM

	OPS	CV	OPS	CV	OPS	CV	OPS	CV	OPS	CV
Yield (Y)	7.72	18.33	2.25	50.13	7.58	9.11	11.31	9.11	12.00	48.67
Plant height (PH)	3.42	10.94	2.75	18.69	7.96	4.68	11.24	4.68	12.00	17.75
Total cladode area (TCA)	6.19	16.17	2.25	39.96	7.30	7.91	11.04	7.91	12.00	39.11
Number of cladodes (NC)	5.97	16.66	2.75	36.50	8.81	8.05	15.42	7.49	12.00	34.47
Cladode thickness (CT)	3.49	21.20	3.00	28.96	8.50	13.88	15.37	13.53	12.00	22.45
Cladode area (CA)	3.72	7.26	2.45	13.58	9.25	2.24	19.58	1.81	96.00	13.05
Cladode length (CL)	2.14	4.96	2.50	6.89	9.46	1.30	19.48	1.10	12.00	6.63
Cladode width (CW)	2.77	5.22	2.10	8.03	9.07	1.67	20.24	1.07	12.00	7.64

The range of plot sizes estimated by modified maximum curvature method was five basic units, ranging from three to eight basic units (Table 2). Hence, experimenters may benefit from a more detailed recommendation for each phenotypic characteristic when aiming to carry out a specific or individual evaluation of one or more traits (Donato et al, 2018), thereby improving factors concerning the study, such as experimental area, time, financial resources, and labor (Cargnelutti Filho et al., 2018).

However, since studies on forage cactus generally investigate all aforementioned vegetative traits, the largest plot size must be used to allow measuring every characteristic, as reported by Donato et al (2008). For this reason, eight basic unit plot sizes estimated by the modified maximum curvature is the one to be used for experiments on forage cactus pear (Guimarães et al., 2019).

Paludo et al. (2015) further explained that the modified maximum curvature method, despite its algebraic precision at determining the optimum plot size, estimates smaller plot sizes than other estimating methods, but with a better R^2. Additionally, this method allows estimating intermediate plot sizes in comparison with pre-established basic unit plot sizes (Facco et al., 2018).

Using Hatheway's method (Hatheway, 1961), plot sizes were estimated as a function of the true difference between two treatment means (%). Owing to the specificity of this method, it is only possible to observe differences in response to the treatment effect if the detectable true difference is equal to or greater than the coefficient of variation (CV) of the measured characteristic (Donato et al., 2018).

The optimum plot size was approximately three basic units, regardless of the evaluated vegetative characteristic (Table 2), with four replications and five treatments. The true detectable difference was based on the coefficient of variation of the vegetative characteristic. Sousa et al. (2016) and Donato et al. (2018) reported that Hatheway's method tends to yield too small plot sizes or broad basic unit plot sizes, which makes the practical use of some plot sizes unfeasible.

Hatheway's methodology allows the experimenter to select the suitable plot size in line with the objective of the study by using a statistical matrix combining factors such as coefficient of variation, true difference (%) between treatment means, number of treatments and number of replications; nonetheless, researchers should be cautious with plot sizes estimated from combinations of these factors, as some estimates are of low practical use (Sousa et al., 2016).

Furthermore, it is possible with Hatheway's method to select the experimental plot based on the experimental area efficiency use. The experimenter can either use larger plots (three basic units) with fewer replications (four) or smaller plots (two basic units) with more replications (ten), with no change in precision when evaluating the yield of 'Gigante' forage cactus pear. This selection criterion defines the smallest experimental area associated with the highest precision by choosing the lowest area efficiency use (Donato et al., 2018).

The linear response plateau model estimated plots with similar sizes across phenotypic characteristics, with a range of two basic units among plot sizes. Eight basic unit plots (3.2 m^2) are recommended for evaluating plant height, total cladode area and yield; for the number of cladodes and cladode thickness, the optimum plot size consisted of nine basic units (3.6 m^2); and for cladode area, length and width, a plot size of 10 basic units is recommended (4 m^2) (Table 2).

Both the linear response plateau and Hatheway's methods estimated plots with similar sizes regardless of the vegetative characteristic. However, plot sizes estimated by the modified maximum curvature method were the most uneven across characteristics. This discrepancy between plot sizes might be linked to either the natural variability of the evaluated trait (Cargnelutti Filhoet al., 2018) or specificity of the method (Donato et al., 2008). The latter is the case of this study.

Several studies have been carried out on the use of the aforementioned methods for estimating the optimum plot size: modified maximum curvature method (Sousa et al., 2016; Cargnelutti Filhoet al., 2018; Guimarães et al., 2019), Hatheway's method (Sousa et al., 2016; Cargnelutti Filhoet al., 2016; Donato et al., 2018) and linear response plateau regression (Leonardo et al., 2014; Sousa et al., 2015; Sampaio Filhoet al., 2019). These studies agree on the dependent relationship between plot size and CV of the characteristic; thus, characteristics with higher variability need larger unit areas to show significant differences between treatments (Donato et al., 2018).

The results presented by these methods were not similar. With the only exception of yield, the linear response plateau yielded a larger plot size than the modified maximum curvature method. The literature has more frequently shown the linear response plateau method than the modified maximum curvature method (Paranaíba et al., 2009; Oliveira et al., 2011; Brito et al., 2012). Concerning the significance of the models, the coefficients were significant with *($0.01 < p \leq 0.05$); **($p \leq 0.01$) and ***($p \leq 0.001$), by the t test. (Figure 1).

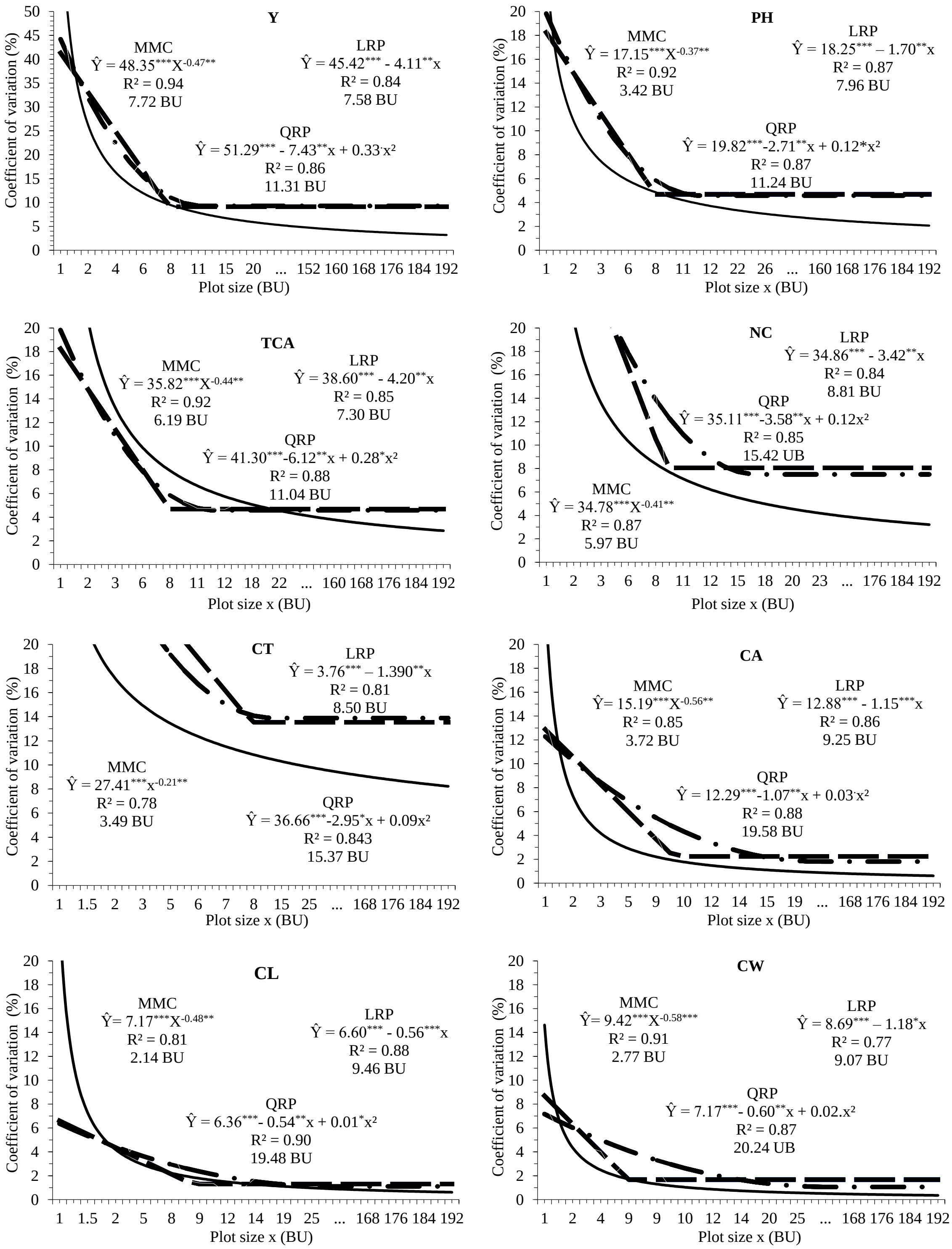

Figure 1. Plot sizes estimated by the regression models: modified maximum curvature-MMC (—), linear response plateau-LRP (---) and quadratic response plateau-QRP (-·-·-), with their respective equations, plot sizes in basic units (BU) and coefficients at '***' ($p \leq 0,001$), '**' ($p \leq 0,01$) and '*' ($0,01 < p \leq 0,05$) of significance level by t test, for the characteristics: Y = yield, PH = plant height, TCA = total cladode area, NC = number of cladodes, CT = cladode thickness, CA = cladode area, CL = cladode length and CW = cladode width

Modified maximum curvature method had the best-fitting regression models, with coefficient of determination (R^2) ranging from 0.81 to 0.94; whereas the linear response plateau method had R^2 ranging from 0.77 to 0.88 (Figure 1). Higher values of R^2 coupled with the significance of coefficients composing the model ensure higher reliability when determining the optimum plot size by the modified maximum curvature method (Figure 1). The best model fitting for this method was also reported by Sousa et al. (2015), Donato et al. (2008) and Viana et al. (2002) for sunflower, banana and cassava, respectively.

The quadratic response plateau regressions estimated larger plot sizes than linear response plateau, modified maximum curvature and Hatheway's methods for 'Gigante' forage cactus pear. Likewise, Oliveira et al. (2014) found larger plots when using quadratic response plateau in comparison with the linear response plateau models for studies on genotypes of banana. According to these authors, the relationship between the increase in plot size and reduction in CV may assume a quadratic behavior. Nonetheless, linear response plateau regression models were better for estimating the optimum plot size.

Complementary results were reported by Peixoto et al. (2011) by comparing the response plateau regression models for estimating plot sizes for experiments with passion fruit. Therefore, based on the parameters that define the quality of the model, coefficient of determination, significance of coefficients and plot size, the authors pointed out the superiority of the linear response plateau model, as similarly observed herein (Figure 1).

The relationship between the experimental precision (CV) and plot size directly varies with the crop and measured characteristic; thus, linear response plateau and modified maximum curvature had the best-fitting models when defining the optimum plot size. Guarçoni et al. (2017) and Donato et al. (2008) reported the best plot size estimated using linear response plateau and modified maximum curvature, respectively.

Silva et al. (2012), using modified maximum curvature, linear response plateau and quadratic response plateau, found different plot sizes for radish. They concluded that plot sizes with 21 to 63 basic units are suitable for an adequate experimental design. Within this range, segmented quadratic response plateau regression models estimated the largest plots, followed by the linear response plateau and modified maximum curvature methods.

With comparison of variances method, an inversely proportional ratio between reduced variances and plot size in basic units is observed. The effect of decreasing variance with increasing plot size has been already reported by several authors (Henriques Neto et al., 2009; Donato et al., 2008; Viana et al., 2002; Vallejo & Mendoza, 1992; Ortiz, 1995). This analysis is the defining point for estimating the optimum experimental plot size.

Through the comparison of variances method, a 96 basic unit plot size was ideal for measuring cladode area since it had lower variance than plots consisting of one, 12, 24 and 48 basic units. As for the remaining characteristics, plot sizes with one, 12, 24, 48 and 96 basic units did not differ from one another with respect to variance; therefore, 12 basic unit plot sizes are recommended as this size has the lowest number of basic units among sizes of equal variances (Table 2).

In studying methods for estimating optimum size of plots, Henriques Neto et al. (2009), Donato et al. (2008), Viana et al. (2002), Vallejo and Mendoza (1992) and Ortiz (1995) found the largest plots by using comparison variances of method for wheat, banana, cassava, potato and banana, respectively. Notwithstanding, studies diverged as to the definition of the most suitable method. Henriques Neto et al. (2009), Vallejo and Mendoza (1992) and Ortiz (1995) considered comparison of variances method as the most reliable method for estimating the optimum plot size, whereas Donato et al. (2008) and Viana et al. (2002) reported the best results with the modified maximum curvature method.

As shown in Table 2, plot size estimates varied with both methods and characteristics. Hatheway's method estimated the lowest number of basic units, with a single plot size for all characteristics, with four replicates and five treatments. The largest plot sizes were estimated with comparison of variances method, with 12 basic unit plots being suitable for most measured characteristics.

Every model evaluated in this study estimated intermediate sizes in relation to predetermined basic units, except for comparison of variances method, which establishes a value of optimum plot size that coincides with what was previously determined.

In trials with ‘Gigante’ cactus pear, characteristics studied herein are normally evaluated, so it is necessary to select optimum plot sizes that meet the minimum requirement for all characteristics. Furthermore, when sizing plots, one must consider the specific nature of the crop regarding morphology, presence of spines and shoot architecture as these are characteristics that hinder data collection in the field.

4. Conclusions

Optimum plot size estimates varied with both methods and measured characteristics.

Quadratic response plateau model estimated the largest plot sizes, whereas the smallest estimates were determined by Hatheway’s method.

Comparison of variances method estimated intermediate plot sizes in comparison with the other method for most measured characteristics.

The modified maximum curvature determined plot sizes that are more consistent with studies with ‘Gigante’ forage cactus.

Ten basic unit plot sizes estimated by linear response plateau model can be used with high precision, practical feasibility for carrying out experiments, and significant optimization of resources.

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CAPÍTULO X

DIDACTIC TOOL FOR EXPERIMENTAL DEMONSTRATION WITH ‘GIGANTE’ FORAGE CACTUS PEAR

(Artigo publicado pelo Journal of Educational Research and Reviews)

ARTIGO 10

Didactic tool for experimental demonstration with 'Gigante' forage cactus pear[10]

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Abstract: To make scientific knowledge easier to grasp, interpret and understand, the researcher must make an effort using didactic resources and innovative tools to meet the purposes of research. The art of representing the scientific knowledge as an alternative to the traditional model renders the pedagogical process more efficient. This work aimed to present a model representing the optimum experimental plot size for 'Gigante' forage cactus pear, defined using the linear response plateau method, by an *in vivo* model with the species *Opuntia brasiliensis* (Willd) Haw. We developed a model with 28 basic units arranged in a 4 x 7 grid of which ten basic units are plants for measurements arranged in a 2 x 5 *grid* or 40 cm^2 with the species *Opuntia brasiliensis*. The *in vivo* model scale, 1:10, represents a ten basic unit optimum plot size (40 cm^2), which in the field corresponds to 4 m^2 of the forage crop. Using the experimental model as a didactic and strategic resource was successful in improving the practical understanding of agronomic concepts; therefore, the *in vivo* model may be developed not only for thesis qualification and defense, but also for any teaching, research and extension environment as an innovative tool.

Keywords: Experimentação, maquete, *Opuntia*.

[10]Artigo publicado pelo Journal of Educational Research and Reviews

INTRODUCTION

Agricultural trials are founded on the statistical definition of a suitable plot size, which is one of the main strategies for increasing experimental precision, reducing error, and improving the reliability of inferences drawn from the experimental design (Sampaio Filho et al., 2019). Generally, one selects a method for estimating the optimum plot size that is easy to use, highly precise and allows an effective visualization of results (Tedford et al. 2017).

However, the success of methods in estimating plot size should not be solely based on the theoretical representation of the results. From a pedagogical standpoint, to make the scientific knowledge easier to assimilate, interpret and effectively understand, the researcher must make an effort through didactic resources and innovating tools to meet the purposes of a study. The art of representing the scientific knowledge as an alternative to the traditional model renders the pedagogical process more efficient (Alves & Barros, 2019).

In defining plot size and shape for field trials, the results are quantitative, with values expressed as a number of basic units or unit area, thereby limiting the practical understanding of the reader. Nonetheless, demonstrating knowledge using an actual didactic instrument enables visually grasping the spatial context provided by a three-dimensional model. In turn, it favors a better understanding between what is observed in the model and what was algebraically estimated (Sharma, 2019).

Aiming at selecting from the family Cactaceae the most similar species to the 'Gigante' cactus pear (*Opuntia ficus-indica* Mill), using morphological, anatomical and physiological characteristics, *Opuntia brasiliensis* (Willd) Haw. was chosen for its importance in representing *Opuntia ficus-indica* Mill (Azevedo et al., 2013). Phyllotaxy of cladodes, modified leaves (spines), parallelocytic stomata, crassulacean acid metabolism (CAM), and arrangement and thickness of epidermis and cuticle were the main characteristics taken into account, which are related to the natural adaptation of the species to arid and semiarid environments (Rosas et al., 2012).

Furthermore, Silva et al. (2001) reported similar stomata frequency between *Opuntia brasiliensis* (Willd) Haw, with 46 stomata mm^{-2}, and *Opuntia ficus-indica* Mill, with 50 stomata mm^{-2}. Therefore, in comparing both species, *Opuntia brasiliensis* can harvest CO_2 as efficiently as *Opuntia ficus-indica*, favoring carbon fixation for photosynthesis and thus positively affecting the vegetative growth.

This study aimed to present a model representing the experimental optimum plot size for ‘Gigante’ forage cactus pear, determined by the linear response plateau method (LRP), using an *in vivo* model with the species *Opuntia brasiliensis* (Willd) Haw.

MATERIAL AND METHODS

The work was conducted in an experimental area at Baiano Federal Institute, campus Guanambi, state of Bahia, Brazil. The soil is a Litolic Neosol and mean annual rainfall and temperature are 670.2 mm and 25.9 °C, respectively.

Based on a blank trial, plants, each one considered a basic unit (BU), were subjected to homogenous agronomic practices throughout the area. For evaluation purposes, eight central rows consisting of 48 plants each were used, totaling 384 ‘Gigante’ forage cactus plants. The following vegetative characteristics were measured in the third production cycle: plant height (m), cladode length (cm), cladode width (cm), cladode thickness (mm), cladode number (unit), cladode area (cm^2), cladode total area (cm^2) and yield ($Mg\ ha^{-1}$). The distribution of the 384 BUs on the area allowed designing 15 specific plot sizes, thereby they fully occupied an area of 153.60 m^2.

The linear response plateau model was defined as:

$$CV_i=\begin{cases}\beta X_0+\beta_1 X_i+\varepsilon i & \text{if, } X_i \leq X_c\\ P+\varepsilon i & \text{if, } X_i>X_c\end{cases},\ i = 1,...15 \qquad (1)$$

where, CV_i is the coefficient of variation between plot sizes X_i; X_i is the plot size in basic units; X_c is the optimum plot size in basic units; P is the coefficient of variation on the plateau; β_0 is the intercept; β_1 is the angular coefficient; and εi is the random error associated with CV_i (Sampaio Filho et al., 2019). The optimum plot size was calculated using the function $X_c=\frac{(\hat{P}-\hat{\beta}_O)}{\hat{\beta}_1}$,where, $\hat{\beta}_0$,$\hat{\beta}_1$ and P are parameters of model (1).

Based on plot sizes (BU) estimated by the linear response plateau method for ‘Gigante’ forage cactus pear, an *in vivo* model was designed with the species *O. brasiliensis*, according to the virtual model built using SketchUp Application (Figure 1A). The growing medium was confined to rectangular-shaped boxes made of wood from a commercial forest of *Pinus* sp. The boxes were 70 cm long, wide, and seven cm in deep. (Figure 1B). A model having the same dimensions as the wooden box was built using marble stone (Figure 1C). A natural growing medium was used at a ratio of 70, 25 and 5% of dirt, sand and cattle manure, respectively.

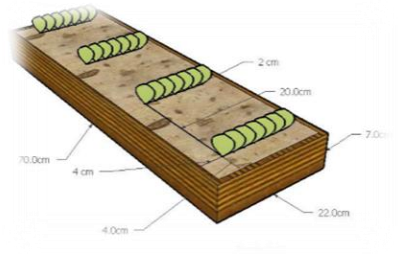

Figure 1A. Schematic design of the box representing the soil and model with the species *O. brasiliensis*

Figure 1B. Wooden box in which the growing medium was placed

Figure 1C. Marble stone used for building the model

Source: materials created by the authors

The cladodes planted in the model were selected based on their vigor, uniformity and overal health, thus reflecting an actual forage cactus pear plantation. Cladodes were collected from a single, representative plant with 28 cladodes (Figure 2A). Afterwards, the cladodes were placed in shade for 15 days for healing the wound resulted from the detachment from the plant, called curing (Figure 2B).

Figure 2A. Representative *Opuntia brasiliensis* plant from which cladodes were collected, after harvesting

Figure 2B. Cladodes selected and left for wound healing - curing

Source: materials created by the authors

Aiming at the maximum similarity between growth and development parameters, the *in vivo* model growing the species *Opuntia brasiliensis* was conducted under soil and climate conditions akin to the field trial with the species *Opuntia ficus-indica*; therefore, an improved didactic comparison between both species in an academic environment was obtained. Statistical procedures for determining plot size in the field as well as *in vivo* were carried out using R (R Development Core Team, 2012).

RESULTS

Using the relationship between the 15 plot sizes estimated on the field trial and their respective coefficient of variation, optimum plot sizes for every measured characteristic were estimated using the linear response plateau method. A 0.9 BU variation occurred across plot sizes. The smallest plot size was for plant height with 8.55 BUs, followed by cladode number (8.81 BUs), yield (8.83 BUs), total cladode area (8.84 BUs), cladode length (9.07 BUs), cladode thickness (9.23 BUs), cladode area (9.27 BUs) and cladode length (9.46 BUs).

However, determining plot sizes is a quantitative discrete process, that is, integer values are used (Guimarães et al., 2019), and one usually measures all aforementioned characteristics in field trials with 'Gigante' cactus pear; therefore, a single plot size should be selected. When conducting agricultural experiments or field trials, it is necessary that the researcher or instructor defines what the experimental basic unit will consist of, thereby aiming at the highest precision by reducing the experimental error. The optimum plot size for *Opuntia ficus-indica* was represented on the model by 10 basic units using the species *O. brasiliensis.* With the *in vivo* model, students should have a better understanding of it. This plot size was selected due to the stabilization of the coefficient of variation, which means an improved use of resources, as illustrated in Figure 3.

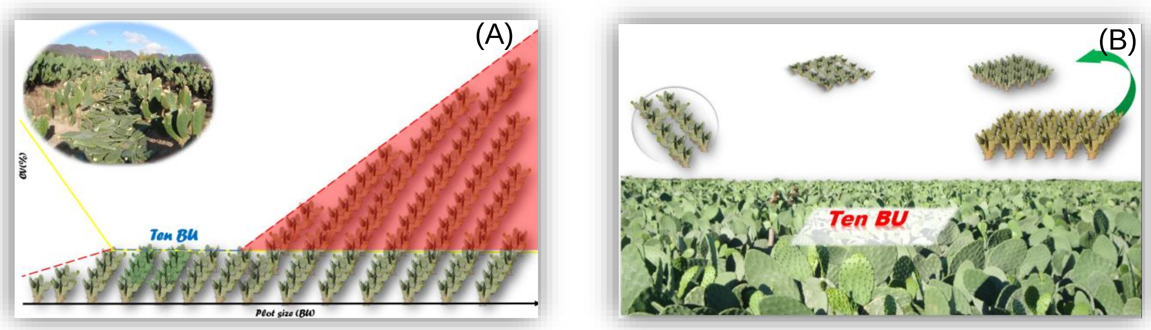

Figure 3. Relationship between the coefficient of variation and the optimum experimental plot sizes (A). Agronomic dynamics for defining the optimum size of experimental plots (B).

The linear response plateau regression model has been used for estimating the optimum plot size for several crops, such as forest species (Bhering et al., 2015), papaya (Celanti et al., 2016), castor bean (Sampaio Filho et al., 2019), among other crops. This method is considered among researchers as an efficient method as it is possible, using a single model, to have precision, an effective visualization, and practical determination.

For concretely visualizing the effect of a field trial, the optimum plot size was defined using the linear response plateau method and, then, this effect was illustrated by the *in vivo* model with the species *Opuntia brasiliensis* in a grid with four rows, seven plants per row, totaling 28 BUs. Plants used for measurements were those within central rows with 10 BUs for all measured characteristics. Figure 4 depicts a didactic-pedagogical representation of the optimum plot size for forage cactus pear determined using the linear response plateau model.

Figure 4. Doctoral thesis qualification using didactic resources for demonstrating the optimum plot size for 'Gigante' forage cactus. Professors, coordinators and students of the professional Master's program signed an informed consent form by which they authorized publishing their images on academic media. **Source:** materials created by the authors

The *in vivo* model used in this study helped students to grasp concepts related to agricultural research; thus, the model is an adequate resource in developing theory and practical classes (Figure 4). Using this method, students followed the growth, development, and crop interactions with the atmosphere. Didactic resources similar to the one presented herein have been developed in several fields of higher education, with focus on increasing accessibility, permanence, and academic success.

DISCUSSION

The use of didactic tools has made the access to information and professional education easier, especially when the model of education in place permits broadening the comprehension of academic contents in an efficient and contextualized manner; hence, using models represents an alternative approach that provides a way of overcoming possible barriers between teaching and learning. Such pedagogical tools are essential during times of insecurity brought about by the Covid-19 pandemic; therefore, building complementary, alternative teaching tools is necessary for education to be successful (Figure 5).

Figure 5. Trends, dynamics, and contextualization of teaching-learning process. Image composed by the authors.

In this regard, Duval (2017) stresses how important building models is as a didactic resource by which the authors involved in it developed numerous abilities from planning, discussion, organization, material acquisition, scheduling, and content. The validation of a differentiated pedagogical model is done by the student body who, according to Stumbles (2018), are immediate agents in a classroom setting, and their basic interests, background diversity, life experience and learning expectations should be met, respected and valued.

The theoretical-practical robustness of research when teaching agricultural sciences must be planned for supporting the professional education at every level. Sinclair et al. (2016), studying knowledge construction and the importance of scientific discussion, added that the development of an innovative, high-quality educational products should be constant over the educational qualification process.

The spread of papers and educational products maximizes knowledge acquisition and breakdown of interpretations; thus, education products should be reproduced, licensed and applied according to multiple needs in academic works (Sarpkaya & Kırdök, 2019). Therefore, a research professor, working with professional qualification, can offer a more concrete practical demonstration of an investigated phenomenon (Alves, 2018).

The search for teaching alternatives has been valued in many multidisciplinary scientific fields (Alves, 2018). Paula & Andreola (2016) identified a strategic dynamic by building models from techniques commonly used by smallholder farmer, thereby promoting a self-sustainable and productive community, where making three-dimensional models is an important and successful didactic-pedagogical tool.

Moreover, Paula & Andreola (2016) reported that group work contributes to the cognitive, psychomotor and affective development of participants and the presentation of a concrete teaching-learning model enabled teachers involved in professional qualification the opportunity of a technical analysis of 3D proposals regarding nature-friendly management and conservation of soil.

Gunčaga et al. (2017) developed an interdisciplinary didactic strategy in building models for physical and virtual demonstration of geometry in a math degree classroom. For the authors, the pedagogical proposal had significant and favorable results in teaching. Besides reaffirming technical concepts in exact and environmental sciences, the model led to a historical and cultural analysis by the academic community. Based on students' opinions, building the model was motivated by the inseparability between theory and practice, thereby allowing a palpable expression of knowledge.

For Alves & Barros (2019), organizing the knowledge as a model allows closely representing the investigated object. A three-dimensional model on a smaller scale, either virtual or physical, serves as support for all areas of knowledge, providing the student with a holistic and isometric vision about the object while giving the teacher insight into students' understanding of the subject being taught.

Creating, describing and interpreting a topic in a critical and innovative way expand one's horizon as well as providing a high-quality professional qualification (Alves, 2018). Such understanding challenges the research professor to seek didactic tools such as models for attaining a better visualization provided by the three-dimensional thematic model, contrasting with the logic of the limited traditionalism that perpetuates in classroom settings with presentation of contents.

Sousa (2014) elaborated didactic-pedagogical workshops on building geographical relief models to aid teachers of several educational levels. According to the researcher, the qualification of students as critical readers of maps is essential for emancipating them from the passive dependence on cartographic works, thus ensuring students the ability of acting as thinkers that can change academia.

As models represent a practical knowledge, they can assume a static or dynamic nature, as reported by Paula & Andreola (2016) and Sousa (2014), respectively. A static model represents a limited observation of objects inserted in the model, while a dynamic model, in addition to observation, allows combining elements composing the model, which favors the development of the reader's critical thinking. However, an *in vivo* model, such as the one presented in this paper, allows a real analysis of a living organism in the face of farming factors directly interfering with the phenotypic expression and development of the crop.

In vivo models illustrate natural characteristics of the species, such as spines, phylotaxy of cladodes, similarity to vegetative growth and reproductive development, as well as interactions with soil and atmosphere, water relations, and defense mechanisms against pathogens (Rosa et al., 2012; Azevedo et al., 2013). Accordingly, these are reliable models for a didactic-pedagogical characterization of the utmost importance for teaching agricultural sciences. They establish a three-dimensional agronomic representation on which *Opuntia brasiliensis* can undergo a detailed analysis, thereby drawing inferences from the crop of interest, *Opuntia ficus-indica* (Figure 4).

This study offers the research professor a teaching tool that contributes to professional and academic qualification, not only by presenting an education product, with wide use in classrooms and other educational settings, but also by improving teaching practice and educational quality. Rôças & Bomfim (2018) emphasize the importance of the criteria used to validate an educational product as these products must emerge in response to a problem, with proper theoretical and statistical support, as performed for the pedagogical proposal reported in this paper.

As discussed by Resende et al. (2002), acquiring and communicating information in agricultural sciences should be open to a broader contribution, including texts, games, models, etc. These didactic tools, particularly for statistics and agricultural sciences, seemingly complex subjects, can constitute a communication bridge for a better understanding, popularization and use of these subjects. These may help to demystify the notion that only a few “geniuses” are able to understand these subjects, and teachers holding this knowledge are often the ones perpetuating this notion. These alternatives would positively contribute to a better qualification of lecturers teaching statistics applied to agricultural sciences, regardless of the level.

The main goal of this study is building an *in vivo* model for representing the optimum plot size for ‘Gigante’ forage cactus pear, further providing teachers and advisors with an actual, practical demonstration of a basic experimental unit, with the maximum representation of the crop. Therefore, we believe that this didactic resource can be used in agricultural sciences not only in teaching statistics but also soil fertility analysis, planting arrangement, irrigation and drainage, pest and disease control, germplasm bank, and species conservation.

FINAL CONSIDERATIONS

Based on the linear response plateau regression method, we developed a rectangular-shaped model consisting of 28 basic units arranged in a 4 x 7 grid of which ten basic units are plants for measurements arranged in a 2 x 5 grid or 40 cm^2 with the species *Opuntia brasiliensis*. The *in vivo* model scale, 1:10, represents a ten basic unit optimum plot size (40 cm^2), which in the field corresponds to 4 m^2 of the forage crop.

Using the experimental model as a didactic and strategic resource was successful in improving the practical understanding of agronomic concepts; therefore, the *in vivo* model can be developed not only for thesis qualification and defense, but also for any teaching, researching and extension environment as an innovative tool.

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Acknowledgements

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APÊNDICES E ANEXOS

Rotina para predição de colheita por RNA pelo software R

```
install.packages('RSNNS')
install.packages('NeuralNetTools')

#apagar memória R
remove(list=ls())

#indicar a pasta de trabalho
setwd("PalmaForrageira")
D=read.table("Palma.txt", head=TRUE)

#análise descritiva

MIN=apply(D,2,min)
MED=apply(D,2,mean)
MAX=apply(D,2,max)
DP=apply(D,2,sd)
CV=100*DP/MED

COR=cor(D)

#juntar os objetos
Desc=rbind(MIN,MED,MAX,DP,CV,COR)

#casualizar o conjunto de dados
id=sample(1:nrow(D))
D2=D[id,]
```

```
#ativar o pacote
library(RSNNS)
?RSNNS

#normatizar os dados
DN=normalizeData(D2, type = "0_1")



#dividir as amostras (treinamento e validação)
DN2=splitForTrainingAndTest(DN[,1:6], DN[,7], ratio = 0.2)

#abrir pacote com a função garson
library(NeuralNetTools)

#criar matrizes
Mat_eqm=matrix(NA,10,100)
Mat_R2=matrix(NA,10,100)



for (neuronios in 1:10){
  for(vezes in 1:100){




rede=mlp(DN2$inputsTrain, DN2$targetsTrain, size = c(neuronios), maxit = 100,
    initFunc = "Randomize_Weights", initFuncParams = c(-0.3, 0.3),
    learnFunc = "Std_Backpropagation", learnFuncParams = c(0.2, 0),
    updateFunc = "Topological_Order", updateFuncParams = c(0),
    hiddenActFunc = "Act_Logistic", shufflePatterns = TRUE, linOut = TRUE)
```

```
pred=predict(rede,DN2$inputsTest)
obs=DN2$targetsTest
eqm=mean((pred-obs)^2)
R2=cor(pred,obs)^2

Mat_eqm[neuronios,vezes]=eqm
Mat_R2[neuronios,vezes]=R2



  }
  print(neuronios)}

mediaeqm=apply(Mat_eqm,1,mean)
dpeqm=apply(Mat_eqm,1,sd)

esteqm=cbind(mediaeqm,dpeqm)
View(esteqm)



#supondo a seleção da rede 5 como a melhor
EQM2=1000000

Mat_Imp=matrix(NA,6,1000)
for(vezes in 1:1000){

rede=mlp(DN2$inputsTrain, DN2$targetsTrain, size = c(5), maxit = 100,
        initFunc = "Randomize_Weights", initFuncParams = c(-0.3, 0.3),
        learnFunc = "Std_Backpropagation", learnFuncParams = c(0.2, 0),
```

```
        updateFunc = "Topological_Order", updateFuncParams = c(0),
        hiddenActFunc = "Act_Logistic", shufflePatterns = TRUE, linOut = TRUE)

pred=predict(rede,DN2$inputsTest)
obs=DN2$targetsTest
eqm=mean((pred-obs)^2)
R2=cor(pred,obs)^2

GARSON=garson(rede)

id=order(as.matrix(GARSON$data$x_names))
Mat_Imp[,vezes]=GARSON$data[id,1]

if(eqm<EQM2){
rede2=rede
EQM2=eqm

}
print(vezes)
}



irmportanciarelativa=cbind(apply(Mat_Imp,1,mean),apply(Mat_Imp,1,sd))
cbind(apply(Mat_Imp,1,mean),apply(Mat_Imp,1,sd))
plotnet(rede2)



barplot(apply(Mat_Imp,1,mean),
       names.arg =colnames(D)[1:6])
```

```
obs=DN2$targetsTest

pred=predict(rede2,DN2$inputsTest)

cor(obs,pred)^2


plot(obs,pred)

cbind(obs,pred)




#####Escala real Valores reais
Norma=NULL
Norma$colMaxima=getNormParameters(DN)$colMaxima[7]
Norma$colMinima=getNormParameters(DN)$colMinima[7]
Norma$type=getNormParameters(DN)$type

#preditos
denormalizeData(pred,Norma)
#observados
denormalizeData(obs,Norma)


modelo=lm (obs~-1+pred)

summary(modelo)
```

Rotina para os modelos de regressão linear, quadrática e interação pelo software R

```
remove(list=ls())
setwd("PalmaForrageira")
D=read.table("parcela útil palma.txt", head=TRUE)

#estatística descritiva

Mínimo=apply(D,2,min)
Média=apply(D,2,mean)
Mediana=apply(D,2,median)
Máximo=apply(D,2,max)
dp=apply(D,2,sd)
cv=100*dp/Média
c=cor(D)
desc=rbind(Mínimo, Média, Mediana, Máximo, dp, cv, c)
plot(D)

#regressão linear simples

#criando o modelo 1 (efeitos lineares)
m1= D$Prod~D$ATC
#fazendo a análise de regressão com a função lm (modelo linear)
aj1=lm(m1)
summary(aj1)
AIC(aj1)
BIC(aj1)
logLik(aj1)
```

```
predito=predict(aj1)
plot(D$Prod,predito)
lm(D$Prod~-1+predito)

#criando o modelo 1 (efeitos lineares)
m2= D$Prod~D$NC
#fazendo a análise de regressão com a função lm (modelo linear)
aj2=lm(m2)

summary(aj2)
AIC(aj2)
BIC(aj2)
logLik(aj2)

#regressão múltipla

#criando o modelo 1 (efeitos lineares)
m3= D$Prod~D$ATC+D$NC+D$AC+D$CC+D$EC+D$LC
#fazendo a análise de regressão com a função lm (modelo linear)
aj3=lm(m3)

#obtendo os resultados
summary(aj3)
AIC(aj3)
BIC(aj3)
logLik(aj3)

#método stepwise
```

```
#parte do modelo completo (com todos os parâmetros)
step(aj3)

#regressão com interação

modelo1=lm(Prod~(CC+LC+EC+Altura+NC+ATC+I(CC^2)+I(LC^2)+I(EC^2)+I(AC^2)+I(NC^2)+I(ATC^2))^2,data=D)
summary(modelo1)

modelo2=step(modelo1)
summary(modelo2)

#fazendo um gráfico de dispersão (observado vs predito)
x=predict(aj1) #valores preditos
y=D1$Prod #valores observados
plot(x,y) #formar gráfico
cbind(x,y) #unir valores

x=D$Prod #valores preditos
y=D$ATC  #valores observados
plot(x,y) #formar gráfico
cbind(x,y) #unir valores


#fazendo um grafico de dispersão (observado vs predito)
x=predict(aj2) #valores preditos
y=D$Prod #valores observados
plot(x,y) #formar gráfico
cbind(x,y) #unir valores
```

```
#gráfico superfície resposta.

aj4=lm(Prod~ATC+EC,data=D)

summary(aj4)

AIC(aj4)


Mat=expand.grid(ATC=seq(min(D$ATC),max(D$ATC),l=20),EC=seq(min(D$EC),max(D$EC),l=2
0))

pred=predict(aj4,newdata=as.data.frame(Mat))

Mat=cbind(Mat,pred)


write.table(Mat,file="Preditos.txt", col.names=F,row.names=F, sep="\t")
```

Rotina para estimativa do tamanho ótimo de parcela pelo método da máxima curvatura modificada pelo software R

```
#Apagar a memória do R
remove(list=ls())
#indicar para o r a pasta de trabalho
setwd("PalmaForrageira")
#Importar os dados
D=read.table(PalmaForrageira.txt",h=T)

X=D[,1]
Y=D[,2]

#Y=sqrt(Y)/mean(Medidas[,6]*Medidas[,5])
plot(X,Y)
#text(0,0,coefficients(m)[2])


m= lm(log10(Y)~log10(X))
print(summary(m))

x=seq(1,max(X),l=100)
a=10^coefficients(m)[1]
b=coefficients(m)[2]

y=a*x^b

lines(x,y)
b=-b
PC=(a^2*b^2*(2*b+1)/(b+2))^(1/(2+2*b))
```

```
Resultado=list()
Resultado$Ajuste=summary(m)
Resultado$Coeficientes=c(a=a,b=-b)
Resultado$PC=PC
Resultado$CV=100*sd(c(D))/mean(c(D))
Resultado$Curva=cbind(x,y)
Resultado
```

Rotina para estimativa do tamanho ótimo de parcela pelo método linear com resposta platô pelo software R

```
remove(list=ls())
D=read.table("PalmaForrageira",h=T)

sink("ResultadoLinear.txt")
Pred1=Pred2=cbind(0:192)
for(i in 2:9){

  print(paste("Analise da variavel ->",colnames(D)[i]))

  x=D[,1]
  y=D[,i]
  plot(x,y)



  #lINEAR plator
  print("Modelo Linear")
  model=nls(y ~ (b0 + b1*x)*(x <= (p-b0)/b1)+(I(p)*(x > (p-b0)/b1)),start=list(b0=20, b1=-3,
p=5),trace=F)


  b0=coefficients(model)[1]
  b1=coefficients(model)[2]
  p=coefficients(model)[3]

  model=nls(y ~ (b0 + b1*x)*(x <= (p-b0)/b1)+(I(p)*(x > (p-b0)/b1)),start=list(b0=b0, b1=b1,
p=5),trace=F)
```

```
  print(summary(model))
  xc=(p-b0)/b1
  print(paste("ponto crítico =", round(xc,4)))
  #anova(model)
  r2=cor(y,predict(model))^2

  plot(x,y,main=paste(colnames(D)[i],r2))
  lines(0:192,predict(model,newdata=list(x=0:192)))
  Pred2=cbind(Pred2,predict(model,newdata=list(x=0:192)))

  print(paste("Coeficiente de determinacao =", round(r2,4)))



  print("---------------------------------------------------------------------")
}

sink()


write.table(Pred2,file = "Lin.txt",col.names=T,row.names=F,sep="\t")
```

Rotina para estimativa do tamanho ótimo de parcela pelo método quadrático com resposta platô pelo software R

```
remove(list=ls())

setwd("PalmaForrageira")

D=read.table("Dados de feijão 2018.txt",h=T)


sink("ResultadoQuadratico.txt")

Pred1=Pred2=cbind(0:200)

for(i in 2:6){


  print(paste("Analise da variavel ->",colnames(D)[i]))


x=D[,1]

y=D[,i]

plot(x,y)




#Quadrático plator

print("Modelo quadrático")

model=nls(y ~ (b0 + b1*x + b2*I(x^2))*(x <= -0.5*b1/b2)+(b0 +I(-b1^2/(4*b2)))*(x > -
0.5*b1/b2),start=list(b0=8, b1=0.05, b2=-0.0025),trace=F)

print(summary(model))

b1=coefficients(model)[2]

b2=coefficients(model)[3]

xc=-0.5 * b1/b2

print(paste("ponto crítico =", round(xc,4)))

#anova(model)

plot(x,y)
```

```
lines(0:160,predict(model,newdata=list(x=0:160)))
Pred2=cbind(Pred2,predict(model,newdata=list(x=0:200)))
r2=cor(y,predict(model))^2
print(paste("Coeficiente de determinacao =", round(r2,4)))
print("--------------------------------------------------------------------")
}
sink()


write.table(Pred2,file = "Quad.txt",col.names=T,row.names=F,sep="\t")
```

Desdobramentos das atividades relacionadas ao estudo de doutorado em Produção Vegetal no Semiárido com a cultura da palma forrageria ‘Gigante’ 2016 – 2020 (IFBAIANO/UNIMONTES)

PÓS-GRADUAÇÃO STRICTO SENSU Mestrado e Doutorado em PRODUÇÃO VEGETAL NO SEMIÁRIDO

Mestrado Profissional Produção Vegetal no Semiárido

INSTITUTO FEDERAL Baiano Campus Guanambi

INSTITUTO FEDERAL AMAZONAS

UFMG

Unimontes

(Bruno Guimarães, 2018)

Redes Neurais Artificiais

Tese de doutorado (UNIMONTES)

Dados gerais do curso

✓Nome do curso: **Redes neurais artificiais para Ciências Agronômicas - *RNACA*;**

✓Eixo tecnológico: Estatística;

✓Características do curso: Tese de doutorado: Bruno Guimarães, sob orientação: Ignacio Aspiazú, Sérgio Donato e Alcinei Azevedo, 2016-2019);

✓Número de vagas: 20 vagas;

✓Valor da inscrição: R$ 30,00 (acadêmico) e R$ 50,00 (profissional);

✓Carga horária total: 20 horas;

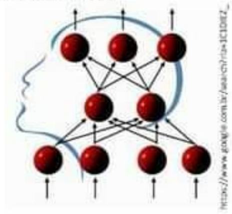
✓Turno das aulas: Diurno, eventualmente noturno para aulas práticas e/ou teóricas;

✓Data: 6 e 7 de março de 2018;

✓Horário das aulas: 08:00 às 12:00 h; 14:00 às 18:00 h;

✓Local das aulas: UNIMONTES- *Campus* Janaúba-MG, sala nova;

✓Organização: Alcinei Azevedo, Nermy Valadares e Ana Clara (UFMG), Bruno Guimarães (Acadêmico UNIMONTES/IF), Ignacio Aspiazú (UNIMONTES) e Sérgio Donato (UNIMONTES, IF-BAIANO).



Objetivos do curso

✓ Oportunizar aos acadêmicos e servidores da UNIMONTES o conhecimento sobre o programa R e a aplicação prática das Redes Neurais Artificiais – *RNAs*;

✓Demonstrar os conteúdos teóricos e práticos acerca dos padrões de *RNAs* no universo agrícola;

✓Organizar, transformar e preparar dados para ajustar modelos de *RNAs* com vistas na estimativa e predição dos fenômenos agronômicos;

✓Apresentar o artigo: **PREDIÇÃO DA PRODUTIVIDADE DE PALMA 'GIGANTE' POR CARACTERES MORFOLÓGICOS E REDES NEURAIS ARTIFICIAIS**, publicado na revista AGRIAMBI, (Tese de doutorado, Bruno Guimarães, orientação: Ignacio Aspiazú, Sérgio Donato e Alcinei Azevedo, 2018).

Perspectivas do curso *RNAs*

✓Conhecer a metodologia dos cálculos matemáticos que envolvem as redes neurais artificiais;

✓Compreender na teoria e na prática os conceitos como *perceptron*, funções de ativação, *backpropagation* (retropropagação) e *gradient descent* (descida do gradiente);

✓Aprender a determinar os caracteres mais importantes na confecção de modelos preditivos;

✓Codificar uma estrutura neural utilizando as diversas formulações;

✓ Entender como as redes neurais podem ser utilizadas no cenário e nas pesquisas agronômicas.

VENHAM CAPACITAR SOBRE *RNACA*!

Garanta sua participação por meio da inscrição no curso *RNACA*

Local da inscrição: UNIMONTES - Av. Reinaldo Viana, 2630, Bairro Bico da Pedra, Caixa Postal 91. CEP: 39440-000. Telefones: Telefone: (77) 99121-4608; (38) 99185-2256.
 - Laboratório de Produção de Grande Culturas, responsável prof. Ignacio Aspiazú.

Documentos necessários:

✓ Cópia do RG;
✓ Pagamento da taxa de inscrição;
✓ Cadastrar Email para envio do material didático (*RNACA*).

Requisitos

O participante do curso *RNACA* deve trazer o notebook com os seguintes programas instalados:

✓ Primeiro tem de instalar o R (https://cran.rproject.org/)

✓ Depois o RStudio (https://www.rstudio.com/products/rstudio/download/)

✓ Depois de instalar os softwares deve instalar os pacotes (Dentro do Rstudio ou R) pelos comandos:

install.packages("RSNNS")
install.packages("NeuralNetTools").

Organizador do curso Redes Neurais para Ciências Agrárias
Bruno Guimarães

Palestrante do curso Redes Neurais para Ciências Agrárias, UNIMONTES, 2018

Palestrante do curso Redes Neurais para Ciências Agrárias

Demonstração dos métodos para estimativa do tamanho de parcela com a palma forrageira

Turma do mestrado profissional do IFBAIANO, 2018.1

1 - Prediction Of ‘Gigante’ Cactus Pear Productivity By Morphological Characters And Artificial Neural Networks, Revista AGRIAMBI.

2 - Regressão linear e quadrática com platô para estimativa do tamanho de parcelas em ensaio experimental com palma ‘Gigante’, Revista Caatinga.

3 - Tamanhos de parcelas para ensaio experimental com a palma forrageira, Revista ASA.

4 - Size of plots for experiments with cactus pear cv. ‘Gigante’, Revista AGRIAMBI.

Qualificação Stricto Sensu na UNIMONTES, 2018.2

Apresentação dos artigos científicos

Rotina para estimativa do tamanho de parcela experimental

Duração 10 horas, no período de 4 a 5 de outubro de 2018.

Estudantes do mestrado em Produção Vegetal no Semiárido (UNIMONTES)

Semana Nacional de Ciência e Tecnologia, 2018.

Curso de qualificação sobre rotinas para predição de colheita e estimativa do tamanho de parcela em palma forrageira. IFBAIANO. 2018.2

Organizador do Dia Técnico sobre a Palma Forrageira

Registro fotográfico e editorial do II Dia de Campo sobre a Palma Forrageira

Banca de defesa de Mestrado *Stricto Sensu*

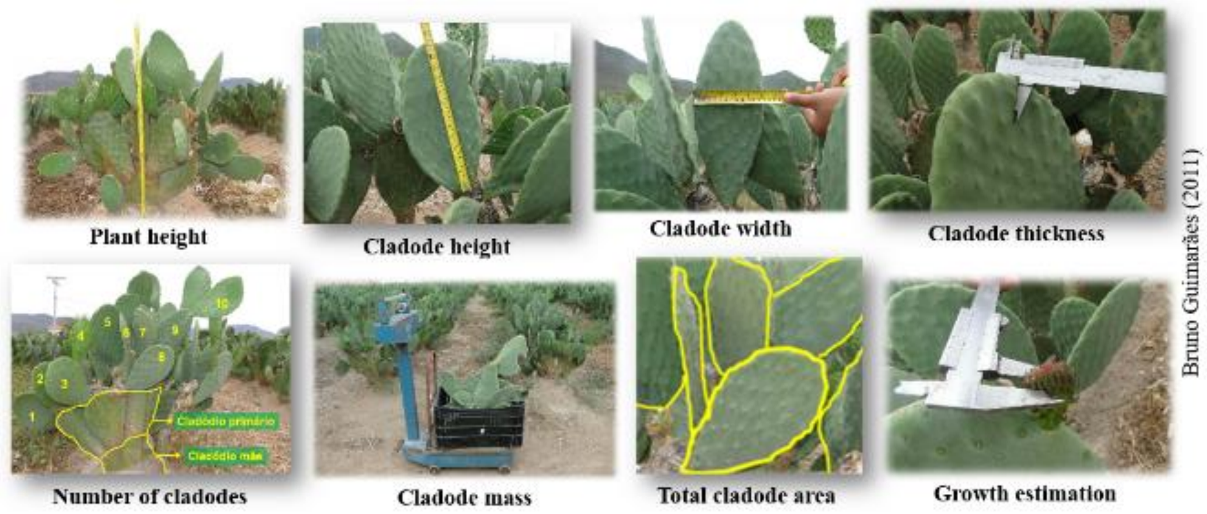
Certificamos que Bruno Vinícius Castro Guimarães atuou como membro titular da banca de Mestrado *Stricto Sensu,* Intitulada: *NORMAS DRIS E VALORES DE REFERÊNCIA PARA PALMA FORRAGEIRA 'GIGANTE' CULTIVADA COM ADUBAÇÃO ORGÂNICA EM CONDIÇÕES SEMIÁRIDAS,* no dia 31 de janeiro de 2019.

Curso: Rotina para estimativa do tamanho de parcela experimental,

duração de 10 horas, 21 de maio de 2019

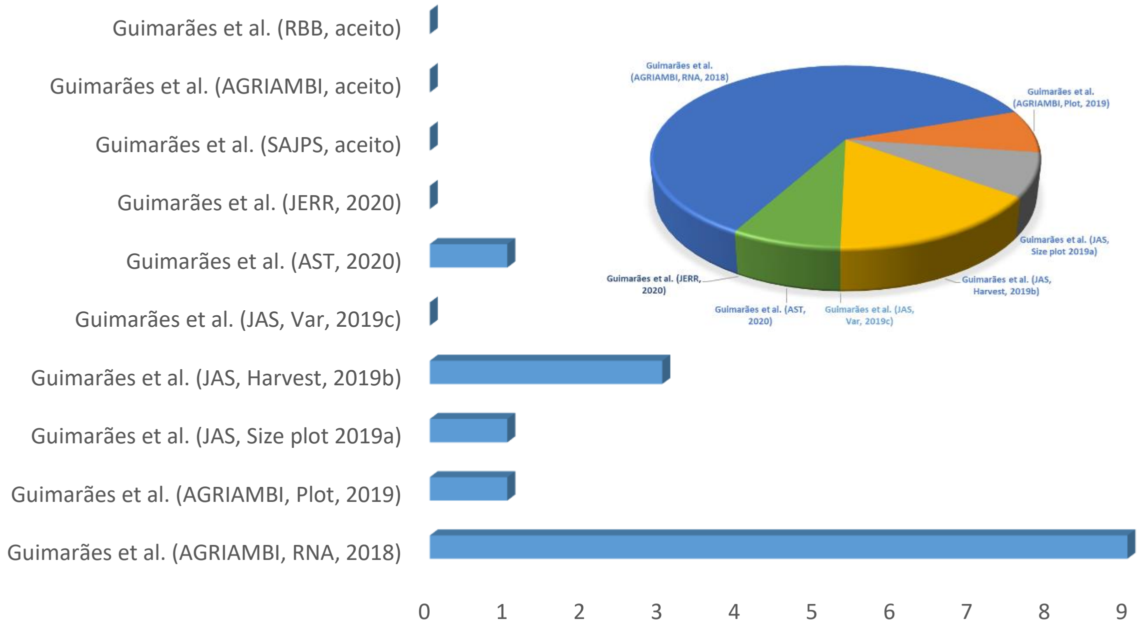
Estudantes do mestrado em Produção Vegetal no Semiárido (UNIMONTES)

Arranjo espacial da palma forrageira, IF-Baiano, Foto: Bruno Guimarães.



Fonte: Elaboração do autor.

CITAÇÕES DOS ARTIGOS DA TESE



Prediction of ‘Gigante’ Cactus Pear Yield by Morphological Characters and Artificial Neural Networks, artigo publicado pela Revista Brasileira de Engenharia Agrícola e Ambiental - AGRIAMBI, 2018 **(RNA);**

Size of plots for experiments with cactus pear cv. Gigante, artigo publicado pela revista Brasileira de Engenharia Agrícola e Ambiental - AGRIAMBI, 2019 **(Plot);**

Methods for Estimating Optimum Plot Size for ‘Gigante’ Cactus Pear, artigo publicado pelo Journal of Agricultural Science – JAS, 2019 **(Size plot);**

Comparison of Methods for Harvest Prediction in ‘Gigante’ Cactus Pear, artigo publicado pelo Journal of Agricultural Science – JAS, 2019 **(Harvest);**

Plot size by the variance comparison method for with 'Gigante' cactus pear, artigo publicado pelo Journal of Agriculture Science – JAS, 2019 **(Var);**

Optimal plot size for experimental trials with Opuntia cactus pear, artigo publicado pela revista Acta Scientiarum.Technology – AST, 2020 **(AST);**

Didactic tool for experimental demonstration with ‘Gigante’ forage cactus pear, artigo publicado pelo Journal of Educational Research and Reviews, 2020 **(JERR);**

Regression plateau for plot size estimation with 'Gigante' forage cactus pear, artigo aceito pelo periódico South African Journal of Plant and Soil, 2019 **(SAJPS);**

Regression models for yield prediction in cactus pear cv. Gigante, artigo aceito pela Revista Brasileira de Engenharia Agrícola e Ambiental – AGRIAMBI, 2018 **(AGRIAMBI);**

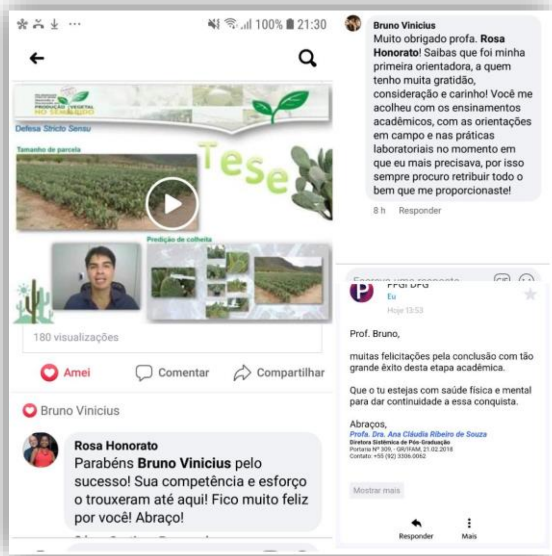
Plot size and shape for field trials with forage cactus pear, artigo aceito pela Revista Brasileira de Biometria, 2020 **(RBB);**

“Neste momento tão complicado que estamos vivendo em esfera global, o desenvolvimento de alternativas necessárias, conscientes e estratégicas possibilitou a continuidade das nossas atividades acadêmicas! Abaixo apresento uma prévia do que foi realizado nesta segunda-feira, dia 30 de março de 2020 - nossa defesa de tese via Skype! Após cinco horas de defesa e muitas tantas outras de preparação, tivemos a sensação do resultado alcançado! Muito obrigado meu Deus por tamanhas bênçãos em minha vida! Agradeço também aos meus orientadores, professores e pesquisadores que contribuíram direta e indiretamente para o sucesso desta obra. Vale agradecer também aos meus familiares e amigos!”

(GUIMARÃES, B. V. C. 2020)

Citações dos artigos da tese

1. https://www.sciencedirect.com/science/article/abs/pii/S037842901930228X
2. file:///C:/Users/User/AppData/Local/Packages/Microsoft.MicrosoftEdge_8wekyb3d8bbwe/TempState/Downloads/Predicting_cone_production_in_clonal_seed_orchard_%20(1).pdf
3. file:///C:/Users/User/AppData/Local/Packages/Microsoft.MicrosoftEdge_8wekyb3d8bbwe/TempState/Downloads/32-42_Estimation_of_cladode_area-Lucena_et_al%20(1).pdf
4. https://www.alice.cnptia.embrapa.br/alice/bitstream/doc/1107158/1/Dissertacao2018.pdf
5. https://www.researchgate.net/publication/335524960_Comparison_of_Methods_for_Harvest_Prediction_in_%27Gigante%27_Cactus_Pear#fullTextFileContent
6. http://periodicos.uem.br/ojs/index.php/ActaSciTechnol/article/view/42579/751375148494
7. file:///C:/Users/User/AppData/Local/Packages/Microsoft.MicrosoftEdge_8wekyb3d8bbwe/TempState/Downloads/Predicting_cone_production_in_clonal_seed_orchard_%20(3).pdf
8. https://www.researchgate.net/publication/337287299_Establishment_of_Sufficiency_Ranges_to_Determine_the_Nutritional_Status_of_%27Gigante%27_Forage_Cactus_Pear-Macronutrients#fullTextFileContent
9. file:///C:/Users/User/AppData/Local/Packages/Microsoft.MicrosoftEdge_8wekyb3d8bbwe/TempState/Downloads/5dc0e430540d6%20(1).pdf
10. file:///C:/Users/User/AppData/Local/Packages/Microsoft.MicrosoftEdge_8wekyb3d8bbwe/TempState/Downloads/5d4a3401cb55a%20(1).pdf



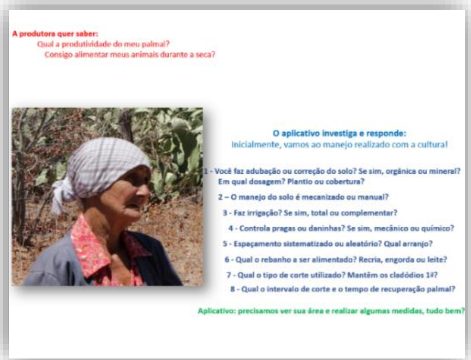
Defesa de tese do doutorado, 30 de março de 2020.

Registro em vídeo da defesa da tese

https://youtu.be/7hnEY-1sSig
https://www.youtube.com/channel/UCDGyvLCJnv9RtTY1YMBMVNQ

Um aplicativo de celular está sendo desenvolvido em um trabalho conjunto que envolve o IF Baiano, a Unimontes, a Universidade Federal de Minas Gerais (UFMG) e o Instituto Federal de Pernambuco (IFPE). O trabalho é desenvolvido pelo professor Bruno Guimarães (IF Amazonas - Campus São Gabriel da Cachoeira), ele é doutorando em Produção Vegetal no Semiárido na Unimontes, com coorientação do professor Sérgio.

Ele trabalhou com equações, modelos de regressão e redes neurais para prever colheitas e determinar tamanho de parcelas. Já como proposta para um pós-doutorado, o professor pretende inserir as informações sobre os sistemas de produção desenvolvidos no IF Baiano, com as informações como adubação e espaçamento, em um aplicativo, tornando a informação mais acessível e mais fácil de ser interpretada pelo produto. (Texto produzido por Thiago Marques).



Demonstração ilustrativa acerca do aplicativo sobre a cultura da palma forrageira.

Plataforma digital para acesso à informação técnica sobre a cultura da palma forrageira. O modelo ilustrativo será desenvolvido durante o estágio de pós-doutoramento da UNIMONTES, 2020.

Fonte: Elaboração do autor.

ARTIGOS PUBLICADOS ADICIONAIS AO ESTUDO DA TESE (2016 – 2020)

1. http://www.conhecer.org.br/enciclop/2016b/agrarias/Estimativa%20e%20tecnicas.pdf
2. http://www.conhecer.org.br/enciclop/2017a/agrar/diagnostico%20socioeconomico%20da%20%20pecuaria.pdf
3. http://www.conhecer.org.br/enciclop/2017a/soc/sustentabilidade%20cultural.pdf
4. http://www.scielo.br/pdf/rbf/v40n5/0100-2945-rbf-40-5-e-962.pdf
5. file:///C:/Users/User/AppData/Local/Packages/Microsoft.MicrosoftEdge_8wekyb3d8bbwe/TempState/Downloads/5dc0e430540d6%20(1).pdf
6. file:///C:/Users/User/Downloads/Establishment_of_Sufficiency_Ranges_to_Determine_t.pdf

AVALIADOR *AD HOC* (2016 – 2020)

Journal of Agricultural Science
Canadian Center of Science and Education

March 8, 2020

Dear Dr. Bruno Vinícius Castro Guimarães,

Thank you once again for reviewing the submission titled "*Impact of Recycled Corn Gluten Meal as Fertilizer for Year-Round Annual Forage Crop Production and Soil Characteristics*". With your help, and based on your detailed and insightful comments, we have now made decision about the manuscript.

I would like to emphasize that I have found your reviews to extremely meticulous, a clear indication of your deep knowledge in Forage Science. *Journal of Agricultural Science* owes its high quality and rigor to the assistance we receive from outstanding scientists and technologists like yourself.

We appreciate your time and effort in reviewing the paper and greatly value your assistance as a reviewer for *Journal of Agricultural Science*. We look forward to future opportunities to collaborate with you in the future.

Best Wishes,

Sincerely,

Anne Brown

On behalf of,
The Editorial Board of *Journal of Agricultural Science*
Canadian Center of Science and Education

International Journal of Physical Sciences

Dear Dr. BRUNO VINICIUS ,

Best regards,

Editorial Office: Journal Review Department

Journal of Agricultural Science
Canadian Center of Science and Education
9140 Leslie St. Suite 110, Beaver Creek, Ontario, L4B 0A9, Canada

October 21, 2019

Federal Institute of Amazonas
Brazil

Dear Dr. Bruno Vinícius Castro Guimarães,

Thank you once again for reviewing the submissions titled "*Agronomic Response of "Prata" Banana to Fertilizer Sources for Organic Management*". With your help, and based on your detailed and insightful comments, we have now made decision about the manuscript.

I would like to emphasize that I have found your reviews to extremely meticulous, a clear indication of your deep knowledge in Fruit Science. *Journal of Agricultural Science* owes its high quality and rigor to the assistance we receive from outstanding scientists and technologists like yourself.

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Best Wishes,

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On behalf of,
The Editorial Board of *Journal of Agricultural Science*
Canadian Center of Science and Education

Journal of Agricultural Science
Canadian Center of Science and Education
9140 Leslie St. Suite 110, Beaver Creek, Ontario, L4B 0A9, Canada
Tel: 1-416-642-2606
Fax: 1-416-642-2608
E-mail: jas@ccsenet.org
Website: www.ccsenet.org

November 7, 2019

Dear Dr. Bruno V. C. Guimarães,

Thank you once again for reviewing the submissions titled "*Measurement of Nutritive Value and Phenolic Compounds in Forage Plants Used in Animal Production*". With your help, and based on your detailed and insightful comments, we have now made decision about the manuscript.

I would like to emphasize that I have found your reviews to extremely meticulous, a clear indication of your deep knowledge in Forage Science. *Journal of Agricultural Science* owes its high quality and rigor to the assistance we receive from outstanding scientists and technologists like yourself.

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Anne Brown

On behalf of,
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Canadian Center of Science and Education

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Tel: 1-416-642-2606
Fax: 1-416-642-2608
E-mail: jas@ccsenet.org
Website: www.ccsenet.org

March 8, 2020

Dear Dr. Bruno Vinícius Castro Guimarães,

Thank you once again for reviewing the submission titled "*Modeling the Growth of Forage Legumes*". With your help, and based on your detailed and insightful comments, we have now made decision about the manuscript.

I would like to emphasize that I have found your reviews to extremely meticulous, a clear indication of your deep knowledge in Forage Science. *Journal of Agricultural Science* owes its high quality and rigor to the assistance we receive from outstanding scientists and technologists like yourself.

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Best Wishes,

Sincerely,

Anne Brown

On behalf of,
The Editorial Board of *Journal of Agricultural Science*
Canadian Center of Science and Education

REVISTA CAATINGA
ISSN 1983-2125 (On-line)
ISSN 0100-316X (Impresso)
Universidade Federal Rural do Semi-Árido

DECLARAÇÃO

O Comitê Editorial da Revista Caatinga da Universidade Federal Rural do Semi-Árido – UFERSA DECLARA para os devidos fins, que o (a) Senhor (a) **Bruno vinicius**, atuou como revisor (a) ad hoc deste periódico, avaliando o artigo ID 9286 no mês de abril de 2020, contribuindo significativamente com os trabalhos da Revista Caatinga.

Mossoró/RN, 18 de abril de 2020.

Editor Chefe

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REVISTA CAATINGA
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Mossoró/RN, 19 de dezembro de 2018.

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Revista Caatinga

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O Comitê Editorial da Revista Caatinga da Universidade Federal Rural do Semi-Árido – UFERSA DECLARA para os devidos fins, que o (a) Senhor (a) **Bruno Vinicius Castro Guimarães**, atuou como revisor (a) ad hoc deste periódico, avaliando o artigo ID 7000 no mês maio de 2018, contribuindo significativamente com os trabalhos da Revista Caatinga.

Mossoró/RN, 23 de maio de 2018.

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Revista Caatinga

DECLARAÇÃO

CONCLUSÕES GERAIS

Os métodos de determinação do tamanho de parcela utilizados neste trabalho apresentam resultados diferentes, pois diferem na sua concepção, contudo, são complementares. De toda forma, as informações utilizadas em cada um deles se baseiam na minimização da variância média de tratamentos e na precisão experimental. Assim, caso seja possível, a consideração de mais de um método é altamente recomendável.

O tamanho da parcela experimental com oito unidades básicas no formato com oito fileiras e uma planta por fileira assegura efetividade na avaliação experimental, pois, essa combinação entre tamanho e formato de parcela além de atender todas as características normalmente avaliadas em estudos com a palma forrageira, decresce a heterogeneidade do solo, com a diminuição do erro experimental, e alcança ganhos significativos sobre a precisão.

Os menores valores de tamanhos de parcelas estimados foram associados ao método da máxima curvatura modificada, enquanto que as maiores estimativas foram conexas aos modelos quadráticos com resposta platô, essa discrepância entre os métodos pode ser atribuída à própria subjetividade, especificidade e singularidade do modelo.

As estimativas do índice de heterogeneidade do solo (b) pelo método de Smith (1938) a partir dos dados do ensaio em branco (EB) e delineamento simulando um experimento em parcelas subdivididas (DPS) e pelo método do coeficiente de correlação intraclasse (CCI) pela proposta de Lin e Binns (1984), foram similares neste estudo, indicando solo de natureza heterogênea na área experimental. O índice (b) devenvolvido por Smith (1938) permeia a maioria dos métodos de determinação do tamanho de parcela e do número de repetições.

Adicionalmente, a partir dos caracteres morfológicos, é possível predizer a produtividade da palma forrageira com alta precisão por meio das RNAs, com coeficiente de determinação (R^2) de 0,87 para a amostra de validação, assegurando o potencial de generalização do modelo.

A análise das características vegetativas: área total dos cladódios; número de cladódios; área, comprimento, espessura e largura dos cladódios por meio de adoção da regressão linear múltipla, interação quadrática ou somente a variável área total dos cladódios pelo emprego da regressão linear simples, permite a predição da produtividade da palma forrageira, com ajuste (R^2_a) em 0,83, 0,76 e 0,74, respectivamente. Isso possibilita quantificar o aporte nutricional e hídrico com uso da palma forrageira para fomentar o planejamento rural no semiárido brasileiro com.

DECLARAÇÃO DE CORREÇÃO DA LÍNGUA PORTUGUESA

UNIVERSIDADE ESTADUAL DE MONTES CLAROS
PRÓ- REITORIA DE PÓS-GRADUAÇÃO
Programa de Pós-Graduação em Produção Vegetal no Semiárido

Unimontes

DECLARAÇÃO

Eu, **ANDRÉIA LEAL CARDOSO MOREIRA**, graduada em Letras Português pela Universidade Estadual de Montes Claros – UNIMONTES, declaro, para os devidos fins, que fiz a ***revisão gramatical de Português*** da tese intitulada: **PREDIÇÃO DE COLHEITA E ESTIMATIVAS DO TAMANHO E FORMATO DE PARCELAS EXPERIMENTAIS PARA PALMA FORRAGEIRA 'GIGANTE'**, do discente **BRUNO VINÍCIUS CASTRO GUIMARÃES**, do Programa de Pós-Graduação em Produção Vegetal no Semiárido, área de concentração em Produção Vegetal, para obtenção do título de Doutor, da Unimontes, campus Janaúba.

Janaúba, 16 de abril de 2020.

CPF: 080.417.136-02

Andréia Leal Cardoso Moreira
Assinatura e CPF do Declarante

Secretaria do Programa

Recebido, ___/___/____

DECLARAÇÃO DE CORREÇÃO DA LÍNGUA INGLESA

DECLARAÇÃO

Eu, BISMARC LOPES DA SILVA, graduado em Agronomia pelo Instituto Federal de Educação, Ciência e Tecnologia Baiano, e inglês acadêmico pela *University of Wisconsin* – River Falls, WI, EUA, declaro para fins que se fizer necessário, que realizei a **revisão gramatical do Inglês** da tese intitulada **PREDIÇÃO DE COLHEITA E ESTIMATIVAS DO TAMANHO E FORMATO DE PARCELAS EXPERIMENTAIS PARA PALMA FORRAGEIRA 'GIGANTE',** do discente **BRUNO VINÍCIUS CASTRO GUIMARÃES**, do programa de pós-graduação em Produção Vegetal no Semiárido, área de concentração em Produção Vegetal, para obtenção do título de Doutor, da Unimontes, campus Janaúba.

Por ser verdade, firmo o presente.

Vitória da Conquista, 17 de Abril de 2020.

CPF: 048.825.955-08

Bismarc Lopes da Silva

Bismarc Lopes da Silva
Engenheiro Agrônomo
Mestrando em Fitotecnia (UESB – Vitória da Conquista-BA)
Inglês Acadêmico – University of Wisconsin – River Falls, WI, EUA

Secretaria do Programa

Recebido, ___/___/___/