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Evaluation of the Directly and Indirectly Effects of the Morpho-Physiological Traits of Sweet Corn Seedlings on Yield with Structural Equation Modeling Partial Least Square (SEM-PLS) Approach

Mısır Fidelerinin Morfo-Fizyolojik Özelliklerinin Verime Doğrudan ve Dolaylı Etkilerinin Yapısal Eşitlik Modellemesinin Kısmi En Küçük Kare (SEM-PLS) Yaklaşımıyla Değerlendirilmesi

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Abstract: Environmental stress factors have a very complex effect on the growth and growth parameters of plants. Therefore, special analytical techniques such as SEM-PLS can better understand the between observational variables and abiotic stress factors. Therefore, the present study was aimed to evaluate the, directly and indirectly, effects of the growth and biochemical parameters of sweet corn seed on yield, which seed primed with different melatonin doses and grown under different soil salinity conditions using the SEM-PLS model. Seeds of sweet corn cultivar Vega F1 were soaked in 0, 50, 100, and 200 µM of melatonin solution for 24 h, and then primed seeds were cultivated under four (0.27, 5.45, 9.00, and 12.32 dSm^{-1}) soil salinity conditions. The study results showed that melatonin directly and positively affected growth parameters (β = 0.502, p <0.05). In contrast, salinity directly and negatively affected growth parameters (β = -0.689, p <0.05). Also, melatonin had a mostly indirect effect (β = 0.623) on biochemical components compared to direct effect (β = -0.277). The indirect effect (β = -0.855) of salinity on biochemical components was more significant than its direct effect (β = 0.244). Finally, the SEM-PLS can be used as a significant tool for understanding the benefits of melatonin and salinity's positive or negative effects through direct and indirect relationships with the mediating variables of growth parameters and biochemical, which are essential to optimize sweet corn yield.

Keywords: SEM-PLS, melatonin, sweet corn, soil salinity, growth parameters

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Öz: Çevresel stres faktörlerin bitkilerin büyüme ve gelişme paraetreleri üzerinde çok karmaşık etkileri bulunmaktadır. Bu nedenle, SEM-PLS gibi özel analitik teknikler gözlemsel değişkenler ile abiyotik stres faktörleri arasındaki ilişkileri daha iyi anlaşılmasını sağlamaktadır. Bu nedenle, farklı toprak tuzluluğu koşullarında ve değişik melatonin dozu ile ön uygulama yapılmış mısır tohumlarının büyüme ve biyokimyasal özelliklerinin verim üzerine doğrudan ve dolaylı olarak etkilerinin değerlendirilmesi amaçlanmıştır. Tatlı mısır çeşidi Vega F1 tohumları 24 saat boyunca 0, 50, 100 ve 200 µM melatonin çözeltilerinde bekletilmiş ve daha sonra ön uygulama yapılmış tohumlar dört (0.27, 5.45, 9.0 ve 12.32 dSm^{-1}) farklı toprak tuzluluğu koşullarında yetiştirilmiştir. Çalışma sonuçlarına göre; melatonin büyüme parametreleri (β = 0.502, p <0.05) üzerinde doğrudan ve pozitif olarak etki göstermiştir. Ancak, toprak tuzluluğu büyüme parametrelerini (β = -0.689, p <0.05) doğrudan ve negatif olarak etkilemiştir. Bununla birlikte, melatonin doğrudan etkiye kıyasla (β = -0.277) biyokimyasal bileşenler üzerine daha çok dolaylı etkilerinin (β = 0.623) olduğu belirlenmiştir. Tuzluluğun biyokimyasal bileşenler üzerine olan dolayı etkisi (β = -0.855) doğrudan etkisinden daha fazla olduğu tespit edilmiştir. Sonuç olarak,, SEM-PLS analizi, tatlı mısır verimini optimize etmek için gerekli olan büyüme ve biyokimyasal değişkenlerin doğrudan ve dolaylı ilişkiler yoluyla melatonin ve tuzluluğun olumlu veya olumsuz etkilerinin anlaşılmasında önemli bir araç olarak kullanılabilir.

Anahtar kelimeler: SEM-PLS, melatonin, tatlı mısır, toprak tuzluluğu, büyüme parametreleri

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INTRODUCTION

Salinity stress (SS) is a critical factor affecting plant growth and contributes significantly to global agricultural productivity losses. Because of its high starch and vitamin content, sweet corn is widely grown in Turkey and other countries. However, sweet corn is susceptible to SS during germination and early shoot formation (Wang et al., 2020). Many physiological and metabolic processes in plants are restricted by SS thermodynamically. It has been widely reported that SS has a detrimental effect on sweet corn crops because it induces oxidative stress and increases soil osmotic pressure (Huang et al., 2019). SS reduces plants' ability to obtain water, referred to as osmotic salinity or water deficit, resulting in shorter plants and lower biomass (Huang et al., 2019). This situation is mainly caused by decreases in the photosynthetic capacity of plants due to the high salt stress. Salt accumulation in the root zone induces osmotic stress and disrupts cell ion homeostasis by increasing the uptake of essential elements such as K^+, Ca^{2+}, Na^+, Cu^{2+}, and Zn^{2+} (Ali et al., 2021).

Seed priming with melatonin (MT) is improved abiotic stress tolerance in plants (Bahcesular et al., 2020; Cao et al., 2019; Li et al., 2017). Several studies have shown that MT 10-200 µM can stimulate the growth and germination of various plants under SS conditions (Simlat et al., 2020; Wang et al., 2016; Xiao et al., 2019; Zhang et al., 2017). However, the results of studies examining the relationship between melatonin treatment and SS were analyzed statistically separately for each treatment's effect on crop yield, while the effects of the MT on the growth processes and physiology in sweet corn have not been fully understood.

The relationship between multifunctional ecology factors and plants was recently studied using multivariate statistical methods such as Standard Equation Modeling (SEM) (Fan et al., 2016; Grace et al., 2009; Hill et al., 2017; Jahan et al., 2019; Lam and Maguire, 2012; Lamb et al., 2011). Compared to multiple regression analysis, SEM can visualize how variables interact in a network concurrently (Lamb et al., 2011). Researchers can use SEM to propose structural relationship models that include direct and indirect relationships between the examined parameters.

In this study, we aimed to replicate a previously tested hypothesis regarding the effect of MT application on sweet corn yields under different soil salinity conditions. We focused on analyzing the effects of MT and SS on sweet corn growth parameters (GP), biochemical composition (BC), and yield (Yi). We hypothesized that the effect of MT application on Yi under SS conditions would be mediated either directly or indirectly by GP and BC. Understanding how these treatment functions interact is critical for elucidating the mechanisms involved in Yi's effect.

MATERIAL AND METHOD

Field Site and Experimental Design

The study was conducted in the plastic greenhouse of Ondokuz Mayis University Agricultural Faculty's Practical Research Field in Samsun, Turkey using Vega F1 variety hybrid sweet corn seeds during July-August 2020. The selected healthy seeds were washed with distilled water, then sterilized for 2 minutes in 1% sodium hypochlorite solution, and finally washed with distilled water to sterilize the entire seed surface. Furthermore, sweet corn seeds were soaked for 24 hours in 0 (distilled water) as a control, 50, 100, and 200 µM of MT solution (denoted as M0, M1, M2, and M3). The soil was collected from a 0-15 cm horizon from the around research center and had a clay-loam texture. The soil's clay, silt, sand, pH, field capacity, and wilting point values were 36%, 17%, 47%, 32.16%, and 19.85%, respectively.

After air-drying the soil, it is sieved using a 2 mm sieve. Thereafter, 2.5 kg of soil is placed in a 15 cm diameter polyethylene plastic pot with a soil density of 1.28 g/cm^3. After soaking the seeds in MT, they were air-dried and then planted into the soil with soil salinity levels of 0.27, 5.45, 9.00, and 12.32 dSm^{-1} (denoted as S1, S2, S3, and S4).

Each pot was placed in a complete randomized block design with three replications of each treatment, totaling 48 experimental pots. Daily monitoring and irrigation with low saline water (ECw = 0.25 dSm^{-1}) are used to replenish soil moisture to field capacity when 40% of available moisture is depleted. Before planting, all pots are fertilized with TSP (Triple Super Phosphate) for phosphorus and AS (Ammonium Sulfate) for nitrogen. During the growth phase of 4-6 sweet corn leaves, the same fertilizer is applied.

Data Collection and Measurement

The study was ended 50 days following the initial planting. The plant samples were then harvested and immediately measured plant height, stem diameter, stem length, number of leaves, root length, and fresh weight. Each plant is separated into leaves, stems, and roots, rinsed until clean with distilled water, and then dried at 70^0 C until it reached a constant weight, and then the weights of the dried leaves, stems, and roots were recorded. Leaf samples of oven-dry plants were ground and passed through a 0.25 mm sieve, then weighed 2 grams each to analyze leaf mineral content. The content of Na^+, K^+, and Ca^{2+} in leaves was performed by the photometer method, and the content of Cu^{2+}, Mn^{2+}, and Zn^{2+} was performed by the inductively coupled plasma method (Optima 2100 DV; Perkin-Elmer, Shelton, CT).

The chlorophyll content was determined using a SPAD handheld chlorophyll meter (SPAD-502, Minolta, Osaka, Japan). Data were collected at six points on perfectly developed leaves, from tip to base, and an average was calculated for each treatment. Similarly, stomata conductivity was determined using a porometer (AP4 Porometer Delta-T, Cambridge, UK).

Suctural Equation Modeling- Partial Least Square (SEM-PLS) Analysis

SEM-PLS is frequently used when the research objective is to predict the relationship between constructs (Fan *et al.*, 2016). In this study, the SEM-PLS analysis technique was used to analyze the theoretical model of the effect of MT applications on sweet corn growth and yield under different soil salinity conditions (Fig. 1).

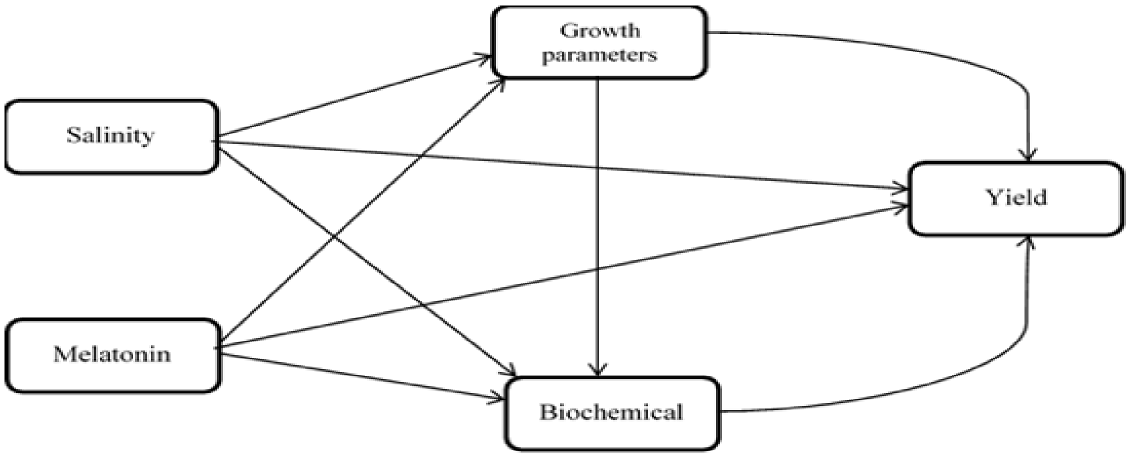

Figure 1. The theoretical model of how melatonin and salinity stress affect growth and biochemical parameters.
Şekil 1. Melatonin ve tuzluluk stresinin büyümeyi ve biyokimyasal parametreleri nasıl etkilediğine dair teorik model.

The effect of MT and SS application on GP, BC and Yi was initially assessed using a two-way ANOVA ($p<0.05$). According to the ANOVA results (data not shown), it was found that the construct variables GP, BC, and Yi showed significant differences to be maintained for further analysis using SEM-PLS. For data analysis, Anderson and Gerbing's two-step modeling method was used according to Anderson et al. (1988). The first stage involves evaluating the outer (reflective) measurement model, while the second stage involves evaluating the outer (structural) measurement model, including hypothesis testing. Additionally, we included a model fit evaluation to validate our proposed model hypothesis further.

To evaluate the reflective model in the first stage; we have used measurement items such as outer loading, reliability composite (CR), and Cronbach's alpha with values greater than 0.70 (Hair et al., 2020), Average Variance Extracted (AVE) with values greater than 0.50 (Hair et al., 2020), and Heterotrait-Monotrait Ratio (HTMT) with a value less than 0.85 (Henseler et al., 2015). The second stage involves the evaluation of the structural model used to test the hypothesis. The proposed model comprises the observed exogenous construct variable, MT, and endogenous construct variables, SS, GP, BC, and Yi. The evaluation of structural models is widely preferred for predicting and validating the relationship between variables. We examine the predictive relevance of the proposed model and the relationships between variables in this modeling. The main criteria for measuring the structural model are the determination path coefficient (R^2) with a value of 0.75 substantial, 0.50 moderate, and 0.25 weak (Hair et al., 2011); the path coefficient (α value) and the T statistical value are considered significant if the comparison of the T-statistic value is greater than (5%; 1.96) (Weir, 2005). Another important method used to measure the structural model is the model's predictive relevance (Q^2) and effect size (f^2), with values of 0.35 substantial, 0.15, moderate, and 0.01 weak (Chin, 1988; Hair et al., 2014).

The Standardized Root Mean Square (SRMR) and Goodness of Fit (GoF) index values were used to evaluate the model's fit. Hu & Bentler (1999) determined that an SRMR value of 0.08 was an acceptable match. Meanwhile, Tenenhaus et al. (2005) proposed a GoF with a value (> 0.9) to close to 1 for general validation of the PLS pathway model. The Chi-Square value was used to evaluate the suitability of the overall model (Hu & Bentler, 1999). A good fit model will give results with a value ($P>0.05$) (Barrett, 2007). Comparative Fit Index (CFI) and Normed Fit Index (NFI) with a value (≥ 0.95) are currently recognized as an indication of the best fit model (Hu & Bentler, 1999). Currently, this index is the most popular measure because it is one of the least affected by sample size. The predictive evaluation of the PLS pathway model and its predictive performance is performed to rule out the possibility of the model overfitting (Shmueli et al., 2016). The Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) indices were used to evaluate the PLS model predictions. RMSE and MAE can range from 0 to ∞, and negatively oriented (Shmueli et al., 2019). All SEM-PLS analyses were conducted using the statistical program SmartPLS 3.2.9.

RESULTS

Evaluation of Reflective Measurement Model

The descriptive statistical results of the measured parameters are given in Table 1.

Outer loading criteria are used to determine the correlation between the construct variables' indicators. For confirmatory and exploratory research, the expected outer loading value is > 0.70 (Hair et al., 2011). An indicator with an outer loading value < 0.70 indicates that the indicator does not significantly correlate with the formed construct variables. Table 2 shows that all indicators have an outer load value of > 0.70 and can be followed by evaluating the formed reflective construction model.

To evaluate a reflective model, we demonstrate the accuracy of measuring required variables in each factor. We evaluated this conceptual model using reliability tests like Cronbach's alpha (α) and composite reliability (CR). In our study, the SEM-PLS measurement model constructs result of Cronbach's alpha (α) and composite reliability (CR) were > 0.70, as shown in Table 2. Additionally, convergent validity can be used to determine the extent of a measure's evaluation of the reflective model. Convergent validity in our study was measured using the AVE, which must have a value > 0.50 to show that the model construction explains more than 50% of the item variance (Hair et al., 2020). As shown in Table 2, all model constructs get AVE values > 0.50 for this conceptual model to accept convergent validity.

The next step is to determine the ratio of the inter-trait correlation with the trait correlation to demonstrate the model construct's discriminant validity. HTMT is the basis for statistically discriminating validity tests (Henseler et al., 2015). The HTMT approach is used to estimate the true correlation of model constructs. Table 3 shows that the HTMT value is significantly lower than the conservative threshold (HTMT < 0.85), the HTMT value close to 1 is considered lower, indicating discriminating validity. As a result, we conclude that the theoretical model construction we propose is appropriate for verifying all adequate evaluation measurement models.

Table 1. Descriptive statistical results of the examined parameters.
Çizelge 1. İncelenen parametrelerin tanımlayıcı istatiksel sonuçları.

Parameters	Samples	Min Value	Max value	Std Er.	Std Dev.	Skewness	Kurtosis
Plant height (cm)	48	31.33	66.00	1.40	9.75	0.09	-0.703
Stem dimeter (mm)	48	4.40	6.80	0.09	0.65	0.02	-0.60
Leaf number (number plant^{-1})	48	4.00	7.00	0.09	0.61	0.53	1.10
Stem length (cm)	48	7.53	21.85	0.56	3.89	0.06	-0.94
Root length (cm)	48	13.50	28.75	0.55	3.78	-0.38	-0.43
Root fresh weight (gpot^{-1})	48	7.00	24.98	0.77	5.35	0.26	-1.26
Root dry weight (gpot^{-1})	48	1.12	3.64	0.11	0.75	-0.58	-0.93
Chlorophyll (SPAD)	48	26.39	73.88	1.73	12.01	-0.08	-0.54
Stomata (mmolm^{-2}s^{-1})	48	79.46	188.00	4.35	30.12	0.61	-0.75
Above ground biomass fresh weight (gpot^{-1})	48	19.31	54.80	1.38	9.58	-0.12	-0.79
Above ground biomass dry weight (gpot^{-1})	48	1.91	10.25	0.33	2.30	-0.04	-1.03
Leaf Na (%)	48	0.22	0.87	0.03	0.18	0.43	-0.87
Leaf K (%)	48	3.81	5.76	0.06	0.45	0.49	-0.33
Leaf Ca (%)	48	1.10	1.82	0.03	0.20	-0.38	-0.97
Leaf K/Na ratio	48	4.92	22.76	0.73	5.05	0.72	-0.49
Leaf Ca/Na ratio	48	1.48	7.28	0.25	1.72	0.58	-0.79
Leaf Cu (ppm)	48	11.11	43.37	1.01	7.01	1.54	2.03
Leaf Zn (ppm)	48	17.08	62.48	1.82	12.61	0.41	-0.99

Table 2. Convergent validity and reliability test of conceptual model.
Çizelge 2. Kavramsal bir modelin yakınsak geçerlilik ve güvenilirlik testi.

Construct	Indicator	Outer Loadings	CR	Cronbach Alpha	AVE
Melatonin	Melatonin	1.000*	1.000*	1.000*	1.000*
Salinity	Salinities	1.000*	1.000*	1.000*	1.000*
Growth Parameters (GP)	Plant height (PH)	0.948*	0.973*	0.967*	0.836*
	Stem diameter (StD)	0.910*			
	Number of leaves (NL)	0.831*			
	Stem length (StL)	0.906*			
	Root length (RL)	0.981*			
	Root fresh weight (RFW)	0.883*			
	Root dry weight (RDW)	0.933*			
Biochemical (BC)	Na^+	-0.880*	0.957*	0.874*	0.802*
	K^+	0.874*			
	Ca^{2+}	0.801*			
	K^{2+}/Na^+	0.957*			
	Ca^{2+}/Na^+	0.959*			
	Cu^{2+}	0.733*			
	Zn^{2+}	0.933*			
	Chlorophyll content (CCI)	0.948*			
	Stomata conductivity (SC)	0.948*			
Yield	Above-ground biomass fresh weight (AGBFW)	0.981*	0.978*	0.967*	0.938*
	Above-ground biomass dry weight (AGBDW)	0.982*			

Note: Number followed by the * are significantly different by $\alpha = 5\%$

Table 3. Discriminant validity test of model: Heterotrait-Monotrait Ratio (HTMT).
Çizelge 3. Modelin ayırt edici geçerlilik testi: Heterotrait-Monottrait Ratio (HTMT).

	Biochemical	Growth Parameters	Melatonin	Salinity
Biochemical				
Growth Parameters	0.664			
Melatonin	0.361	0.509		
Salinity	0.611	0.702	0.000	
Yield	0.683	0.754	0.474	0.686

Evaluation of Structural Measurement Model

To improve understanding of structural model evaluation, we examine the proposed model's predictive relevance and the relationships between constructs. The standard estimate of the path coefficient describes the effect in the model construct between variables. The path coefficient value was used to determine the significance level of the relationship hypothesis between model constructs in the SEM-PLS regression analysis. The path coefficient represents the expected variance in the endogenous constructs for the exogenous variant. The greater the path coefficient value is shown, the more significant the effect on the endogenous latent structure (Chin, 1988). All of our hypothesized structural path coefficients demonstrated significantly different significance at the level ($p < 0.05$). Our results show that all proposed hypotheses were validated and accepted. As shown in Table 4, the application of MT has a significant positive effect on Yi ($\beta = 0.002$, $p < 0.05$), whereas the application of SS has a significant negative effect on Yi ($\beta = -0.005$, $p < 0.05$). MT has a negative effect on BC ($\beta = -0.277$, $p < 0.05$), with SS having a negative effect on BC ($\beta = 0.244$, $p < 0.05$). In contrast, MT has a positive effect on GP ($\beta = 0.502$, $p < 0.05$), having a negative effect on GP ($\beta = -0.689$, $p < 0.05$). Analysis of the path coefficient provides a comprehensive interpretation and can be carried out in applying the conclusions.

Table 4. Hypothesized Path coefficients and p-values of the model.
Çizelge 4. Modelin varsayımsal Path katsayıları ve p değerleri.

Hypothesized Path models			Standardized Beta (β)	Mean	SD	T Statistic
Melatonin	→	Yield	0.002*	0.005	0.029	4.281
Salinity	→	Yield	-0.005*	-0.002	0.030	12.034
GP	→	Yield	0.751*	0.741	0.075	34.37
BC	→	Yield	0.248*	0.260	0.063	3.935
Melatonin	→	BC	-0.277*	-0.279	0.056	2.605
Salinity	→	BC	0.244*	0.243	0.072	8.979
GP	→	BC	1.241*	1.238	0.069	17.857
Melatonin	→	GP	0.502*	0.501	0.072	4.959
Salinity	→	GP	-0.689*	-0.695	0.061	11.353

Note: Number followed by the * are significantly different by $\alpha = 5\%$

SEM-PLS analysis can be used to deduce causal relationships between variables in complex data sets. As shown in Table 5, the application of MT to sweet corn seeds planted under SS conditions could be identified using the SEM-PLS model of complete path coefficients to explicitly test the direct, indirect, and total effects on each variable. Standardized values on these coefficients can help compare paths better. MT application has a significant positive direct effect on GP, but SS has a significant direct negative effect on GP with their respective values ($\beta = 0.502$ and -0.689, $p < 0.05$). Meanwhile, MT and SS were more dominant, with their respective values affecting BC indirectly ($\beta = 0.623$ and -0.865, $p < 0.05$). The total effect of MT on Yi of sweet corn plants was significantly positive ($\beta = 0.465$, $p < 0.05$) mediated by BC and GP. In contrast, the total effect of SS on sweet corn Yi has a negative significance ($\beta = -0.674$, $p < 0.05$) mediated by BC and GP. Direct and indirect effects support the total effect of MT and SS on Yi. These results are supported by the construct variables relationship, which has a very strong relative impact, as shown by measuring R^2, Q^2, and f^2 in Table 6.

Table 5. The estimated total effect, direct effects and indirect effects on the endogenous latent variables and the model's p-values.

Çizelge 5. İçsel gizli değişkenler üzerine tahmini doğrudan, dolaylı ve toplam etkiler ve modelin p değerleri.

Path models			Direct (β)	Indirect (β)	Total (β)
Melatonin	→	Yield	0.002	0.463*	0.465*
Salinity	→	Yield	-0.005	-0.669*	-0.674*
GP	→	Yield	0.751*	0.307*	1.058*
BC	→	Yield	0.248*	0	0.248*
Melatonin	→	BC	-0.277*	0.623*	0.346*
Salinity	→	BC	0.244*	-0.855*	-0.612*
GP	→	BC	1.241*	0	1.241*
Melatonin	→	GP	0.502*	0	0.502*
Salinity	→	GP	-0.689*	0	-0.689*

Note: Number followed by the * are significantly different by $\alpha = 5\%$

Table 6. Predictive relevance and accuracy of the conceptual model.

Çizelge 6. Kavramsal modelin tahmine dayalı uygunluğu ve doğruluğu.

Endogenous Construct	R^2	Q^2	Relationship	f^2	Effect Size
GP	0.728	0.601	MT →GP	0.926	Strong
			SS → GP	0.744	Strong
BC	0.914	0.725	GP → BC	0.854	Strong
			MT → BC	0.461	Strong
			SS→BC	0.250	Weak
Yi	0.981	0.911	BC →Yield	0.276	Weak
			GP → Yield	1.368	Strong
			MT → Yield	0.276	Weak
			SS → Yield	0.231	Weak

Note : MT = Melatonin; SS = Salinity; GP = Growth Parameters; BC= Biochemical; Yi = Yield of Sweet Corn; R^2= Coefficient of Determination; Q^2 = Predictive relevance of Model; f^2 = effect size.

The Fit of the Model and Predictive Evaluation

Although the SEM-PLS does not explicitly address model fit, some researchers propose several important indices for evaluating the model structure's suitability such as SRMR, GoF/GFI, Chi-Square, CFI, NFI, RMSE and MAE (Kline, 2015). According to Table 7, our study's SRMR value of 0.072 indicates that the data measured by the proposed hypothetical model is competent (Hu & Bentler, 1999). The GoF/GFI model criteria are 0.903; the closer to 1, the proposed model hypothesis is more competent (Tenenhaus et al., 2005).

Table 7. Goodness of fit index summary.

Çizelge 7. Uygunluk indeks sonuçları.

Index	Estimated model
SRMR	0.072
GoF/GFI	0.903
Chi-Square	1100.619 (P>0.05)
CFI	0.95
NFI	0.96

The Chi-Square value was 1100.619 (P>0.05), meanwhile the CFI and NFI values were 0.95 and 0.96, respectively, which showed that the conceptual model had a good fit. The RMSE and MAE values in our study indicate the predictive model of evaluation (Table 8). The RMSE value ranges from 0.925 to 1.063, while the MAE value is between 0.844 and 0.925. This value is considered suitable for selecting the best prediction model among the alternative models (Sharma et al., 2018). The predicted value will be closer to the path model hypothesis proposed if the indicated value is lower. Following a thorough evaluation of the outer (reflective) and inner (structural) models and the fit model and SEM-PLS path model prediction, it was determined that all of the hypotheses we proposed were statistically significant and verifiable.

Table 8. Predictive evaluation index of the models.

Çizelge 8. Modellerin tahmine dayalı değerlendirme indeksi.

	RMSE	MAE
BC	1.022	0.867
GP	0.925	0.844
SS	1.063	0.925
Yi	0.945	0.86

Note : SS = Salinity; GP = Growth Parameters; BC= Biochemical; Yi = Yield of Sweet Corn; RMSE= Root Mean Square Error; MAE= Mean Absolute Error.

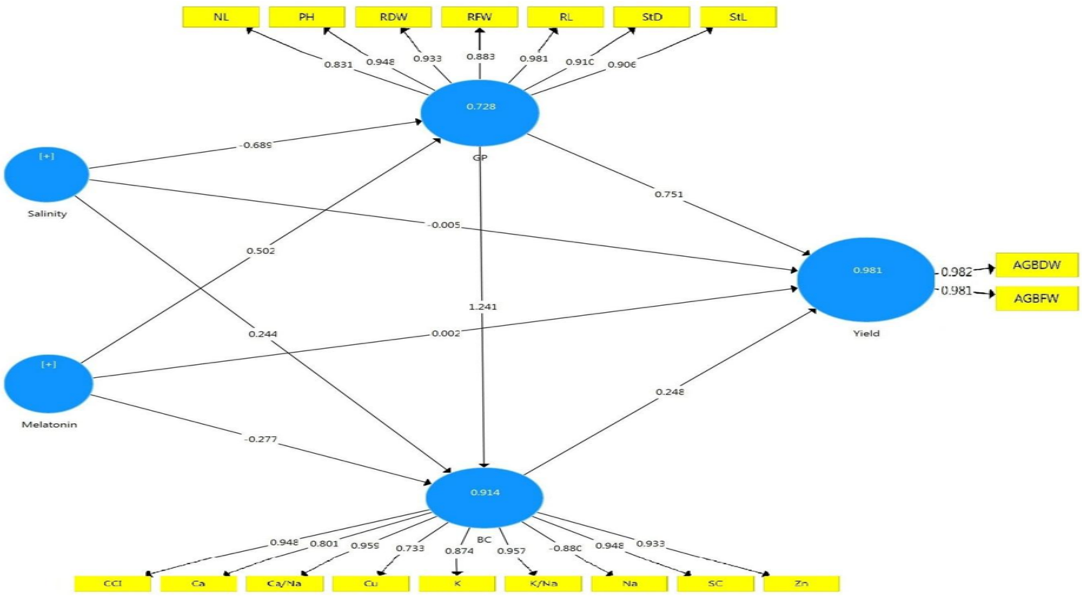

Figure 2. Results of structural equation model analysis.

Şekil 2. Yapısal eşitlik modelinin analiz sonuçları.

The results of the SEM-PLS analysis support the hypothesis of the conceptual model that we propose (Fig. 2). The model can understand the direct and indirect effects of applying MT to the soil under SS conditions on Yi. Besides, this study fills a gap in the literature by examining the effect of MT and SS on Yi, such as through GP and BC-mediated effects. The two treatments used in this study, MT and SS, affect GP, BC, and Yi through a complex series of relationships (Fig. 2). The optimal model for Yi demonstrates that the application of MT has a direct positive effect, whereas the application of SS has a direct negative effect. Soaking sweet corn seeds in MT or SS affected Yi construct variables such as above-ground biomass fresh weight and above-ground biomass dry weight.

DISCUSSION

Each MT and SS treatment directly affected Yi and a negative indirect effect through the GP variable with the indicator characters PH, NL, RFW, RL, SFW, StD, and StL. Several previous studies have shown that the increase in SS directly inhibits seed germination, root elongation, plant growth and results in plant death (Isayenkov and Maathuis, 2019; Numan et al., 2018; Qin et al., 2019), but growth inhibition is overcome by applying MT. Liang et al. (2019) reported that when plants are subjected to abiotic stress, MT up to 200 µM can consistently increase plant height and biomass. Moreover, many studies have shown that MT can increase root length and weight in corn (Yoon et al., 2019). Our analysis confirmed this finding. All indicators representing the GP variable decreased in SS conditions that increased to 12.32 dSm^{-1}. Nonetheless, the application of MT at a concentration of 100-200 μM m reduced damage caused by SS conditions. In a recent study, MT can be considered an IAA-like hormone regulating plant growth and development (Wang et al., 2016). According to the results of the SEM-PLS analysis, the GP variable has a direct positive effect on the BC variable, which then has the same effect on Yi. The linear increase in plant growth increases BC activity by mediating biosynthetic and photosynthetic-related gene experimentation. Thus, MT directly affects the GP variable by encouraging sweet corn growth, similar to the BC variable.

Each MT and SS treatment had an indirect positive and negative effect on Yi, respectively, via the BC variable with the indicator characters Ca^{2+}, Cu^{2+}, K^+, Na^+, Zn^{2+}, Ca^{2+}/Na^+, K^+/Na^+, CCI, and SC. Salt toxicity is one of the most common and severe types of stress damage to germinating seeds. In this study, SS treatment from 0.27 to 12.32 dSm^{-1} could increase Na^+ and Ca^{2+} content and significantly decrease K^+ content. SS treatment has an indirect effect on plant physiological processes in response to SS. Therefore, MT plays an important role in regulating plant physiological processes. MT significantly decreased Na^+ accumulation and increased K^+ content in corn shoots grown in SS (Jiang et al., 2016), which is consistent with our findings. However, we observed an indirect effect of MT on the BC indicator's characteristics in the form of Ca^{2+}, Cu^{2+}, K^+, Na^+, Zn^{2+}, Ca^{2+}/Na^+, and K^+/Na^+. These results may be due to MT concentration, which functions as an antioxidant with the same concentration but under different environmental stresses.

Salinity conditions significantly affect the occurrence of photosynthesis in higher plants (Mbarki et al., 2018). However, it has been demonstrated that the application of MT increases the chlorophyll content and conductivity of stomata during the photosynthetic process under SS conditions (Dai et al., 2020; Li et al., 2017). These results confirm our findings that SS treatment of 12.32 dSm^{-1} can reduce chlorophyll content and stomatal conductivity (data not shown). However, the application of MT at a concentration of 200 μM M increased chlorophyll content and stomatal conductivity by 26% and 21%, respectively (data not shown). SS conditions in our study have an indirect negative effect on the photosynthesis process associated with toxic ions, which reduces the concentration of CO_2 between cells and causes damage to photosynthetic electron transport affecting physiological processes (Acosta-Motos et al., 2017). Meanwhile, MT application had a beneficial effect on stomata by increasing their chlorophyll content and leaf area. The efficiency of photosynthesis in stressed plants suggests that MT functions as a protective mechanism that compensates for the low demand for NADPH (Liu et al., 2020). Additionally, the increase in photosynthetic efficiency is because MT can boost the efficiency of phytochemicals and transcripts of photosynthesis-related genes and protect photosynthetic organs (Erland and Saxena, 2018). As a result, the effect of MT protection on photosynthesis efficiency in plants is highly dependent on the concentration of MT.

Our proposed hypothetical model (Fig. 1) establishes a relationship between variables associated with complex constructs. Despite the small size of our dataset, it enables us to detect and confirm relationships between construct variables. However, some possibilities prevent us from detecting the relationship down to the construct variables' character indicators. We developed our SEM-PLS model for this study using hypotheses from previous research. Finally, it is critical to recognize the highly complex relationship between the effects of MT and SS applications on Yi. GP and BC are critical in mediating the effects of MT and SS on Yi. As a result, we argue that fully exploiting the beneficial effects of MT via direct and indirect relationships to the mediating variables GP and BC is critical for crop yield optimization.

CONCLUSIONS

This study aims to set up a conceptual framework model for understanding the relationship mechanism of MT and SS applications to investigate the mediating role of GP and BC on Yi. This study shows that SS has a indirect (negative effect on Yi, but sweet corn seed priming with MT direct positive effect on Yi. The consisting variables of PH, RL, CCI, Ca/Na, K/Na, and Zn had the most causal effect on above-ground biomass fresh and dry weight of sweet maize under seed priming with melatonin doses. According to the path diagram, biochemical parameters were more important for the AGBDW and AGBFW of sweet maize than the growth parameters, which means that the seedling of the sweet maize was more sensitive to biochemical parameters than the growth parameters. Finally, due to the mediation of GP and BC, seed priming with MT under SS conditions can have positive results, although with a weak effect on Yi. As a result, we conclude that the SS constraint on sweet corn cultivation can be overcome by seed priming MT via GP and BC to boost sweet corn Yi's improvement.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DECLARATION OF AUTHOR CONTRIBUTION

Bhaskara Anggarda Gathot Subrata; Resources, Writing, Statistical Analysis**. Mehmet Sait Kiremit:** Writing-Original draft preparation, Investigation, Statistical analysis. **Elif Öztürk;** Investigation, Methodology**. İsmail Sezer:** Methodology, Supervision. **Hakan Arslan:** Investigation, Methodology, Supervision. **Hasan Akay;** Methodology.

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