MINISTÉRIO DA EDUCAÇÃO
UNIVERSIDADE FEDERAL DE SERGIPE
PRÓ-REITORIA DE PÓS-GRADUAÇÃO E PESQUISA
PROGRAMA DE PÓS-GRADUAÇÃO EM AGRICULTURA E BIODIVERSIDADE

FILMES DE PARTÍCULAS DE ÓXIDO DE CÁLCIO E SILÍCIO EM CAMPO E CASA DE VEGETAÇÃO, NA AVALIAÇÃO DE DÉFICIT HÍDRICO E APRENDIZAGEM DE MÁQUINAS NA PREDIÇÃO DA PRODUTIVIDADE DE ABÓBORA 'MINI JACK'

GENILZA ALMEIDA DA GRAÇA

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Tese apresentada à Universidade Federal de Sergipe, como parte das exigências do Curso de Doutorado em Agricultura e Biodiversidade, área de concentração em Agricultura e Biodiversidade, para obtenção do título de "Doutora em Ciências".

Orientador
Prof. Dr. Luiz Fernando G. de O. Júnior

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APROVADA em 24 de julho de 2026.

Dra. Aline Vasconcelos de Almeida	(UFS)
Dr. Marcelo Augusto Gutierrez Carnelossi	(UFS)
Dr. Thiago Lima da Silva	(IFS)
Dr. Steven A. Sargent	(UF)

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Prof. Dr. Luiz Fernando Ganassali de Oliveira Júnior
(Orientador)

SÃO CRISTÓVÃO
SERGIPE – BRASIL

A Deus, pela dádiva da vida
Dedico

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BIOGRAFIA

Genilza Almeida da Graça, filha de Manoel Messias da Graça e Maria Rosilene Almeida, nasceu no povoado Algodão, Nossa Senhora Aparecida, Sergipe, em 13 de julho de 1995.

Iniciou e concluiu o ensino fundamental na Escola Municipal Dr. José Jairson das Graças, no Colégio Estadual Miguel das Graças e no Colégio Estadual João Salônio.

Concluiu o ensino médio no Colégio Estadual João Salônio no ano de 2012, no município de Nossa Senhora Aparecida, Sergipe.

Em agosto de 2013, iniciou o curso técnico em Agroecologia no Instituto Federal de Educação, Ciência e Tecnologia de Sergipe, concluindo-o em 2015.

Em abril de 2015, ingressou no curso superior de Engenharia Agronômica da Universidade Federal de Sergipe, obtendo o título de Engenheira Agrônoma em 2019.

Em abril de 2022, concluiu o curso de Mestrado em Agricultura e Biodiversidade na Universidade Federal de Sergipe.

Em agosto de 2022, iniciou o curso de Doutorado em Agricultura e Biodiversidade na Universidade Federal de Sergipe, concluindo-o em julho de 2026.

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ARTIGO 1

LISTA DE ABREVIATURAS, SÍMBOLOS E SIGLAS

$^1O_2$	Oxigênio singleto
ABS/CS0	Fluxo de absorção de energia por seção transversal
ABS/RC	Fluxo de absorção de energia por centro de reação
APX	Ascorbato Peroxidase
CaO	Óxido de Cálcio
CAT	Catalase
Chl *a*	Clorofila *a*
Chl *b*	Clorofila *b*
Chl total	Clorofila total
Chl *a/b*	Razão entre clorofila *a* e clorofila *b*
DFABS	Força motriz fotossintética baseada na absorção
DI0/CS0	Fluxo de dissipação de energia por seção transversal
DI0/RC	Fluxo de dissipação de energia por centro de reação
DS	Déficit hídrico (*Drought Stress*)
ET0/ABS	Rendimento quântico do transporte de elétrons
ET0/CS0	Fluxo de transporte de elétrons por seção transversal
ET0/RC	Fluxo de transporte de elétrons por centro de reação
ET0/TR0	Eficiência do transporte de elétrons após o aprisionamento
ETo	Evapotranspiração de referência
LR	Regressão Linear (*Linear Regression*)
MAE	Erro absoluto médio (*Mean Absolute Error*)
MI	Índice de maturação (*Maturation Index*)
ML	Aprendizado de máquina (*Machine Learning*)
M0	Inclinação inicial normalizada do transiente de fluorescência
OEC	Complexo de evolução do oxigênio (*Oxygen-Evolving Complex*)
OJIP	Transiente polifásico da fluorescência da clorofila *a*
PEP	Produção estimada por planta
PIABS	Indice de desempenho fotossintético
PIABST	Índice de desempenho total baseado na absorção
PSI	Fotossistema I
PSII	Fotossistema II
QA	Quinona A
r	Coeficiente de correlação de Pearson
R^2	Coeficiente de determinação
RC/ABS	Densidade de centros de reação ativos por fluxo de absorção
RC/CS	Densidade de centros de reação ativos por seção transversal
RE0/RC	Fluxo de elétrons até os aceptores finais do PSI por centro de reação
RF	Floresta Aleatória (*Random Forest*)
RMSE	Raiz do erro quadrático médio (*Root Mean Squared Error*)
ROS	Espécies Reativas de Oxigênio

Si	Silício
SMOreg	Regressão por Otimização Mínima Sequencial
SOD	Superóxido Dismutase
SVR	Regressão por Vetores de Suporte (*Support Vector Regression*)
TR0/CS0	Fluxo de energia aprisionada por seção transversal
TR0/RC	Fluxo de energia aprisionada por centro de reação
TSS	Sólidos solúveis totais (*Total Soluble Solids*)
TTA	Acidez total titulável (*Total Titratable Acidity*)
VI	Fluorescência variável relativa na etapa I
VJ	Fluorescência variável relativa na etapa J
VK	Fluorescência variável relativa na etapa K
WD	Déficit hídrico (*Water Deficit*)
WEKA	*Waikato Environment for Knowledge Analysis*
WW	Condição hídrica adequada (*Well-Watered*)

RESUMO

GRAÇA, Genilza Almeida da. **Filmes de partículas de óxido de cálcio e silício em campo e casa de vegetação, na avaliação de déficit hídrico e aprendizagem de máquinas na predição da produtividade de abóbora 'Mini Jack'.** São Cristóvão: UFS, 2026. 77p. (Tese – Doutorado em Agricultura e Biodiversidade).*

As mudanças climáticas têm intensificado a frequência e a severidade dos períodos de seca, ampliando os riscos à produção agrícola e a necessidade de estratégias capazes de aumentar a tolerância das culturas ao déficit hídrico. Nesse contexto, filmes de partículas à base de óxido de cálcio (CaO) e o silício (Si) apresentam potencial para modular respostas fisiológicas e reduzir os efeitos do estresse, enquanto o aprendizado de máquina permite integrar informações biológicas e agronômicas para a predição do desempenho produtivo. Este estudo avaliou os efeitos do CaO e do Si na mitigação do déficit hídrico em plantas de abóbora 'Mini Jack' (*Cucurbita moschata*), considerando respostas fisiológicas, bioquímicas, de crescimento e produtivas, bem como o potencial de algoritmos de aprendizado de máquina na predição da produtividade, sendo estruturado em três artigos. No primeiro artigo, foram avaliadas diferentes concentrações de CaO (0; 2,5; 5 e 7,5%) sob irrigação plena e déficit hídrico (66% e 100%). A aplicação de CaO modulou o funcionamento fotoquímico e o desempenho produtivo, com destaque para a concentração de 5%, que favoreceu o transporte de elétrons, preservou a eficiência fotoquímica e proporcionou melhor desempenho produtivo, enquanto a concentração de 7,5% apresentou efeitos menos favoráveis, demonstrando a importância do ajuste da concentração do filme. No segundo artigo, foram avaliadas as aplicações isoladas e combinadas de Si e CaO sob diferentes regimes hídricos. O déficit hídrico comprometeu o crescimento e alterou os pigmentos fotossintéticos, a fluorescência transiente da clorofila *a* e as respostas osmóticas e antioxidantes. O CaO isolado favoreceu a manutenção da área foliar sob déficit hídrico, enquanto a combinação Si + CaO aumentou os índices de clorofila, preservou o funcionamento fotoquímico e reduziu o acúmulo de prolina e a atividade de CAT e APX, indicando menor pressão oxidativa e uma estratégia predominantemente preventiva de proteção do aparato fotossintético. No terceiro artigo, os algoritmos Regressão Linear, Random Forest e SMOreg foram avaliados na predição da produtividade a partir de conjuntos progressivamente integrados de pigmentos, parâmetros OJIP, características biométricas e variáveis de manejo. Os pigmentos isolados apresentaram baixa capacidade preditiva, enquanto a incorporação dos parâmetros OJIP aumentou o desempenho dos modelos, com destaque para o Random Forest. A integração de informações fotoquímicas, pigmentares e biométricas proporcionou o melhor desempenho preditivo, com superioridade do SMOreg, demonstrando que a complementaridade biológica entre os preditores foi determinante para a representação da produtividade. Em conjunto, os resultados demonstram que o CaO e sua associação com Si constituem estratégias promissoras para modular as respostas de plantas de abóbora 'Mini Jack' ao déficit hídrico, enquanto a integração entre ecofisiologia vegetal e aprendizado de máquina amplia a capacidade de relacionar manejo, funcionamento fotossintético, crescimento e produtividade.

Palavras-chave: *Cucurbita moschata*, deficiência hídrica, fluorescência da clorofila *a*, silício, óxido de cálcio, aprendizado de máquina.

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* Comitê Orientador: Luiz Fernando Ganassali de Oliveira Júnior (Orientador), Aline Vasconcelos de Almeida (Coorientadora).

ABSTRACT

GRAÇA, Genilza almeida da. **Calcium Oxide and Silicon Particle Films under Field and Greenhouse Conditions for Assessing Water Deficit and Machine Learning-Based Prediction of 'Mini Jack' Pumpkin Yield.** São Cristóvão: UFS, 2022. 77p. (Thesis -Doctor of Science in Agriculture and Biodiversity).*

Climate change has intensified the frequency and severity of drought periods, increasing risks to agricultural production and the need for strategies capable of enhancing crop tolerance to water deficit. In this context, calcium oxide (CaO)-based particle films and silicon (Si) have the potential to modulate physiological responses and alleviate the effects of stress, while machine learning enables the integration of biological and agronomic information for predicting crop productivity. This study evaluated the effects of CaO and Si on mitigating water deficit in 'Mini Jack' pumpkin (*Cucurbita moschata*) plants, considering physiological, biochemical, growth, and productivity responses, as well as the potential of machine learning algorithms for productivity prediction. The study was structured into three articles. In the first article, different CaO concentrations (0, 2.5, 5, and 7.5%) were evaluated under two irrigation regimes (66 and 100% of crop water requirements). CaO application modulated photochemical functioning and productivity performance, with the 5% concentration promoting electron transport, preserving photochemical efficiency, and improving yield. In contrast, the 7.5% concentration resulted in less favorable responses, highlighting the importance of optimizing particle film concentration. In the second article, the individual and combined applications of Si and CaO were evaluated under different water regimes. Water deficit impaired plant growth and altered photosynthetic pigments, the chlorophyll *a* fluorescence transient, and osmotic and antioxidant responses. CaO alone contributed to maintaining leaf area under water deficit, whereas the Si + CaO combination increased chlorophyll indices, preserved photochemical functioning, and reduced proline accumulation As well as CAT and APX activities, indicating lower oxidative stress and a predominantly preventive strategy for protecting the photosynthetic apparatus. In the third article, Linear Regression, Random Forest, and SMOreg algorithms were evaluated for productivity prediction using progressively integrated datasets comprising pigments, OJIP parameters, biometric traits, and management variables. Pigments alone showed low predictive capacity, whereas the incorporation of OJIP parameters improved model performance, with Random Forest showing the best results. The integration of photochemical, pigment-related, and biometric information provided the highest predictive performance, with SMOreg outperforming the other algorithms, demonstrating that biological complementarity among predictors was critical for accurately representing productivity. Overall, the results demonstrate that CaO and its combination with Si are promising strategies for modulating the responses of 'Mini Jack' pumpkin plants to water deficit, while the integration of plant ecophysiology and machine learning enhances the ability to relate crop management, photosynthetic functioning, growth, and productivity.

Keywords: *Cucurbita moschata*, water deficit, chlorophyll *a* fluorescence, silicon, calcium oxide, machine learning.

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* Guidance Committee: Luiz Fernando Ganassali de Oliveira Júnior (Advisor), Aline Vasconcelos de Almeida (Adjunct advisor).

1. INTRODUÇÃO GERAL

As mudanças climáticas têm intensificado a frequência e a severidade dos períodos de seca, ampliando os riscos à produção agrícola, especialmente em regiões caracterizadas pela alta taxa de evapotranspiração e irregularidade pluviométrica (IPCC, 2023). Entre as culturas de importância alimentar e econômica, as espécies do gênero *Cucurbita* destacam-se pela diversidade de usos, valor nutricional e adaptação a diferentes condições de cultivo (Salehi *et al.*, 2019).

Entretanto, a redução da disponibilidade hídrica pode comprometer o crescimento, o funcionamento fotossintético e o desempenho produtivo das cucurbitáceas, tornando necessária a adoção de estratégias capazes de aumentar a tolerância das plantas à limitação hídrica (Flores-León *et al.*, 2026).

O déficit hídrico desencadeia alterações em diferentes níveis de organização da planta. A redução do estado hídrico limita a expansão celular, as trocas gasosas e a assimilação de carbono, alterando o equilíbrio entre a energia luminosa absorvida e sua utilização nos processos fotoquímicos e metabólicos (Gupta; Rico-Medina; Caño-Delgado, 2020; Qiao *et al.*, 2024). Como consequência, podem ocorrer alterações nos pigmentos fotossintéticos, no funcionamento dos fotossistemas e no transporte de elétrons, além do aumento da produção de espécies reativas de oxigênio e da ativação de mecanismos osmóticos e antioxidantes (Hasanuzzaman *et al.*, 2020; Mittler *et al.*, 2022). Essas respostas estão funcionalmente interligadas e sua intensidade depende da severidade e da duração do estresse, bem como da capacidade de aclimatação da planta.

Nesse contexto, estratégias de manejo capazes de preservar o funcionamento fotossintético e reduzir os danos provocados pelo déficit hídrico apresentam relevância agronômica. O silício (Si) tem sido associado à melhoria das relações hídricas, à manutenção da atividade fotossintética e à modulação do metabolismo antioxidante em plantas submetidas a estresses abióticos (Coskun *et al.*, 2019; Xu; Guo; Liu, 2022).

Paralelamente, filmes de partículas à base de óxido de cálcio (CaO) podem modificar as propriedades ópticas e térmicas da superfície foliar, contribuindo para a fotoproteção e a manutenção do desempenho fisiológico das plantas sob condições ambientais adversas (Oliveira *et al.*, 2021; Oliveira Junior *et al.*, 2026). Entretanto, a eficiência dos filmes depende da concentração aplicada, uma vez que a proteção contra o excesso de radiação deve ocorrer sem restringir a disponibilidade de luz necessária à fotossíntese (Oliveira *et al.*, 2021).

Apesar dos avanços obtidos com o uso isolado dessas estratégias, ainda são limitadas as informações sobre a aplicação combinada de Si e CaO, particularmente quanto aos efeitos sobre o funcionamento fotoquímico, os pigmentos fotossintéticos, o ajustamento osmótico e o metabolismo antioxidante sob déficit hídrico. A compreensão integrada dessas respostas é necessária para determinar se a associação entre os compostos favorece a manutenção da eficiência fotoquímica e reduz a intensidade das alterações fisiológicas e bioquímicas desencadeadas pela limitação hídrica.

Além disso, a elevada quantidade de informações geradas pelas avaliações ecofisiológicas representa um desafio analítico, uma vez que a produtividade resulta da interação entre condições ambientais, práticas de manejo e processos fisiológicos que atuam em diferentes escalas temporais (Ansarifar; Wang; Archontoulis, 2021).

Nesse sentido, o aprendizado de máquina (*machine learning* – ML) apresenta potencial para explorar relações complexas entre variáveis e contribuir para a predição da produtividade. Na agricultura, esses métodos têm sido empregados principalmente com informações meteorológicas, edáficas, agronômicas e de sensoriamento remoto (Van Klompenburg; Kassahun; Catal, 2020; Benos *et al.*, 2021). A incorporação direta de indicadores ecofisiológicos ainda é comparativamente menos explorada, embora estudos demonstrem o potencial de informações relacionadas à atividade fotossintética e à fluorescência da clorofila na construção de modelos preditivos (Ding *et al.*, 2022; Varghese *et al.*, 2023). A integração

progressiva de parâmetros OJIP, pigmentos fotossintéticos, características biométricas e variáveis de manejo pode ampliar a representação biológica da produtividade e permitir avaliar como a natureza das informações utilizadas no treinamento influencia o desempenho de algoritmos com diferentes estruturas de aprendizagem.

Embora o uso de filmes de partículas e do silício tenha demonstrado potencial para atenuar os efeitos de estresses abióticos, ainda existem lacunas quanto à compreensão de seus efeitos sobre o funcionamento fisiológico de abóbora 'Mini Jack' sob diferentes condições hídricas.

Os efeitos de diferentes concentrações de CaO sobre o aparato fotossintético e o desempenho produtivo da cultura, bem como as respostas fisiológicas e bioquímicas decorrentes da aplicação isolada e combinada de Si e CaO, permanecem pouco compreendidos. Além disso, ainda são limitadas as informações sobre a utilização integrada de parâmetros fotoquímicos, pigmentares, biométricos e de manejo na predição da produtividade.

Diante desse contexto, este trabalho teve como objetivo avaliar os efeitos do CaO e do Si na mitigação do déficit hídrico em plantas de abóbora 'Mini Jack', considerando respostas fisiológicas, bioquímicas, de crescimento e produtivas, bem como avaliar o potencial do aprendizado de máquina para predizer a produtividade a partir de diferentes níveis de informação biológica e agronômica.

2. REVISÃO DE LITERATURA

2.1 Cultura da abóbora 'Mini Jack'

As abóboras pertencem à família Cucurbitaceae, considerada uma das mais importantes entre as hortaliças cultivadas mundialmente, abrangendo espécies com elevado valor econômico, nutricional e social (Paris, 2016). Dentre as espécies cultivadas, *Cucurbita moschata* Duchesne destaca-se pela ampla adaptação a diferentes condições ambientais, elevada rusticidade e grande diversidade genética, sendo utilizada tanto para consumo in natura quanto para processamento industrial (Paris, 2016; Salehi *et al.*, 2019). Além disso, a cultura apresenta elevada importância econômica em países de clima tropical e subtropical devido à sua versatilidade de uso e elevada aceitação no mercado consumidor (Da Graça *et al.*, 2024).

Nos últimos anos, a demanda por cultivares de frutos pequenos e com características específicas tem aumentado significativamente, acompanhando mudanças nos padrões de consumo, agregação de valor e exigências de mercado (Loy, 2004; Salehi *et al.*, 2019).

Nesse contexto, a cultivar 'Mini Jack' apresenta características diferenciadas, incluindo frutos de menor tamanho, formato uniforme, elevada atratividade visual e maior praticidade para comercialização e consumo doméstico (Da Graça *et al.*, 2024). Adicionalmente, frutos menores podem representar vantagens relacionadas ao armazenamento, ao transporte e à redução de perdas pós-colheita (Loy, 2004; Da Graça *et al.*, 2024).

A cultivar 'Mini Jack' tem sido utilizada tanto para consumo alimentar quanto para fins ornamentais, apresentando potencial de expansão comercial devido às características físico-químicas dos frutos e à possibilidade de agregação de valor ao produto final. Entretanto, apesar do potencial agronômico dessa cultivar, informações relacionadas aos seus aspectos ecofisiológicos ainda permanecem limitadas, especialmente sob condições de estresse abiótico (Da Graça *et al.*, 2024).

Estudos envolvendo o crescimento e o desenvolvimento da cultivar demonstraram modificações importantes durante o desenvolvimento dos frutos, incluindo alterações em tamanho, massa fresca, coloração, firmeza e parâmetros fisiológicos associados ao metabolismo respiratório. Durante o processo de desenvolvimento, observou-se aumento progressivo no crescimento dos frutos até aproximadamente 15 dias após a antese, seguido por estabilização dos parâmetros biométricos, indicando proximidade da maturidade fisiológica (Da Graça *et al.*, 2024).

Além das alterações relacionadas ao crescimento, processos fisiológicos associados à atividade fotossintética e ao metabolismo energético desempenham papel essencial na produtividade da cultura. A manutenção da integridade funcional do aparato fotossintético constitui fator determinante para o desenvolvimento vegetal adequado, principalmente sob condições ambientais adversas (Taiz *et al.*, 2017).

Embora a cultura apresente relativa adaptação a ambientes tropicais, sua produtividade pode ser significativamente reduzida em situações de limitação hídrica, uma vez que alterações na disponibilidade de água interferem diretamente no crescimento vegetal, no metabolismo celular e na eficiência dos processos fotossintéticos (Flores-León *et al.*, 2026).

2.2 Déficit hídrico e respostas fisiológicas em cucurbitáceas

A disponibilidade de água constitui um dos principais fatores responsáveis pela manutenção do crescimento, desenvolvimento e produtividade das culturas agrícolas (Farooq *et al.*, 2009; Taiz *et al.*, 2017). Entretanto, alterações nos padrões climáticos globais, associadas ao aumento da frequência e intensidade dos períodos de seca, têm ampliado os impactos do déficit hídrico sobre sistemas agrícolas em diferentes regiões do mundo (IPCC, 2023).

O déficit hídrico pode ser definido como uma condição em que a disponibilidade de água no solo torna-se insuficiente para suprir a demanda transpiratória das plantas, resultando em alterações fisiológicas, bioquímicas e metabólicas capazes de comprometer o desempenho vegetal (Hura; Hura; Ostrowska, 2023). A intensidade dos danos provocados depende de diversos fatores, incluindo duração do estresse, estádio fenológico, espécie vegetal e capacidade de adaptação fisiológica (Gupta; Rico-Medina; Caño-Delgado, 2020).

Em cucurbitáceas, a limitação hídrica provoca alterações em processos relacionados ao crescimento vegetal, por exemplo, reduzindo a expansão foliar, área foliar, diminui o acúmulo de biomassa e, consequentemente, o comprimento das plantas (Saadaoui *et al.*, 2023). A redução do crescimento ocorre principalmente devido à menor turgescência celular, reduzindo processos de divisão e expansão celular (Gupta; Rico-Medina; Caño-Delgado, 2020).

Além das alterações morfológicas, o déficit hídrico afeta diretamente a atividade fotossintética (Sampaio-Filho *et al.*, 2026). Em condições de baixa disponibilidade hídrica, o fechamento estomático reduz a assimilação de CO_2 e limita a disponibilidade de aceptores de elétrons no processo fotossintético. Como consequência, ocorre sobrecarga do aparato fotossintético, aumentando a probabilidade de danos aos fotossistemas, reduzindo assim a eficiência do transporte de elétrons (Zivcak *et al.*, 2014; Sampaio-Filho *et al.*, 2026).

A redução na utilização de energia luminosa promove aumento da pressão de excitação sobre o fotossistema II, favorecendo a formação excessiva de espécies reativas de oxigênio (ROS), incluindo radical superóxido (O_2^-), peróxido de hidrogênio (H_2O_2) e radical hidroxila (OH) (Mittler, 2002). O acúmulo dessas moléculas pode causar danos oxidativos em lipídios, proteínas, pigmentos fotossintéticos e membranas celulares, comprometendo o metabolismo vegetal (Mittler, 2002; Yadav *et al.*, 2021).

Entretanto, plantas possuem mecanismos fisiológicos capazes de reduzir os danos induzidos pelo déficit hídrico, incluindo ajustes osmóticos, ativação de sistemas antioxidantes e modificações relacionadas à eficiência fotoquímica (Osman *et al.*, 2022). Recentemente, estudos têm demonstrado que a manutenção da funcionalidade do aparato fotossintético pode representar uma estratégia mais eficiente de tolerância ao estresse quando comparada exclusivamente à ativação de mecanismos antioxidantes, uma vez que a preservação do fluxo eletrônico reduz a própria formação de espécies reativas de oxigênio (Mittler, 2002; Sampaio-Filho *et al.*, 2026).

2.3 Aparato fotossintético e fluorescência da clorofila *a*

A fotossíntese constitui um dos processos fisiológicos mais importantes para o crescimento e desenvolvimento vegetal, sendo responsável pela conversão da energia luminosa em energia química utilizada na síntese de compostos orgânicos (Taiz *et al.*, 2017). Esse

processo ocorre principalmente nos cloroplastos e envolve uma série de reações fotoquímicas e bioquímicas altamente coordenadas (Taiz *et al.*, 2017). A eficiência da fotossíntese depende da integridade estrutural e funcional dos fotossistemas, bem como do adequado fluxo de elétrons ao longo da cadeia transportadora (Taiz *et al.*, 2017; Kalaji *et al.*, 2016).

As reações fotoquímicas ocorrem nos tilacoides dos cloroplastos e envolvem dois complexos proteicos principais: o fotossistema II (PSII) e o fotossistema I (PSI). O PSII atua inicialmente na absorção da energia luminosa e na oxidação da água, liberando elétrons, prótons e oxigênio molecular (Taiz *et al.*, 2017; Kalaji *et al.*, 2016). Os elétrons liberados são transferidos ao longo da cadeia transportadora até o PSI, onde ocorre a redução final do NADP+, possibilitando posteriormente a síntese de carboidratos durante as reações do ciclo de Calvin (Taiz *et al.*, 2017; Kalaji *et al.*, 2016).

A eficiência do transporte de elétrons é fundamental para a manutenção do equilíbrio energético celular (Kalaji *et al.*, 2016). Alterações ambientais, especialmente aquelas associadas ao déficit hídrico, podem provocar limitações no fluxo eletrônico e aumentar a pressão de excitação sobre os centros de reação, favorecendo a dissipação excessiva de energia e a geração de espécies reativas de oxigênio (ROS) (Zivcak *et al.*, 2014).

Nesse contexto, a fluorescência da clorofila *a* tem sido amplamente utilizada como ferramenta rápida, não destrutiva e altamente sensível para a avaliação da funcionalidade do aparato fotossintético (Kalaji *et al.*, 2016; Strasser; Tsimilli-Michael; Srivastava, 2004). Essa técnica baseia-se na capacidade das moléculas de clorofila emitirem parte da energia absorvida na forma de fluorescência quando a energia luminosa não é totalmente utilizada em processos fotoquímicos ou dissipada como calor (Strasser; Tsimilli-Michael; Srivastava, 2004).

Entre os métodos disponíveis, a análise da fluorescência transiente rápida da clorofila *a*, conhecida como curva OJIP, destaca-se pela capacidade de fornecer informações detalhadas sobre o comportamento do transporte de elétrons nos fotossistemas (Stirbet; Govindjee, 2011). A denominação OJIP refere-se às etapas observadas durante a emissão de fluorescência: O (fluorescência inicial), J, I e P (fluorescência máxima), representando eventos sucessivos relacionados à redução dos componentes da cadeia transportadora de elétrons (Strasser; Tsimilli-Michael; Srivastava, 2004).

As alterações na forma da curva OJIP permitem identificar mudanças específicas no funcionamento fotoquímico induzidas por condições de estresse. Sob condições ideais, a transferência eletrônica ocorre de maneira eficiente, promovendo menor acúmulo de energia nos centros de reação. Entretanto, em situações de estresse hídrico, frequentemente são observadas alterações nos transientes de fluorescência associadas à redução da eficiência fotoquímica e ao aumento da dissipação energética (Kalaji *et al.*, 2016; Strasser; Tsimilli-Michael; Srivastava, 2004).

Diversos parâmetros derivados da análise OJIP têm sido empregados para a interpretação das respostas fisiológicas das plantas. Entre eles, destaca-se o parâmetro M0, que representa a inclinação inicial normalizada do transiente de fluorescência e está relacionado à velocidade de fechamento dos centros de reação do PSII. Valores elevados de M0 geralmente indicam maior pressão sobre os centros fotoquímicos e aumento do estresse fisiológico (Strasser; Tsimilli-Michael; Srivastava, 2004; Chen *et al.*, 2016).

Os parâmetros VK e VJ também apresentam elevada relevância na avaliação do aparato fotossintético. O aumento de VK está associado a alterações no complexo de evolução do oxigênio (OEC), indicando possíveis danos à estrutura responsável pela fotólise da água (Strasser; Tsimilli-Michael; Srivastava, 2004). Já os aumentos em VJ podem refletir acúmulo de quinona A reduzida (QA^-), sugerindo limitações no transporte eletrônico entre os aceptores do PSII (Strasser; Tsimilli-Michael; Srivastava, 2004).

Parâmetros relacionados ao transporte eletrônico, como ET0/TR0 e ET0/ABS, também são amplamente utilizados. O parâmetro ET0/TR0 representa a eficiência com que elétrons capturados pelos centros de reação são transferidos ao longo da cadeia transportadora, enquanto ET0/ABS expressa o rendimento quântico do transporte eletrônico por energia absorvida.

Reduções nesses parâmetros frequentemente indicam comprometimento da eficiência fotoquímica e menor utilização da energia absorvida (Strasser; Tsimilli-Michael; Srivastava, 2004).

Além disso, índices integrativos derivados do teste JIP, como o índice de desempenho fotossintético (PIABS), permitem avaliações mais abrangentes da funcionalidade do aparato fotossintético, integrando os processos de absorção de energia luminosa, aprisionamento de energia pelos centros de reação ativos e transporte de elétrons ao longo da cadeia fotoquímica (Strasser; Tsimilli-Michael; Srivastava, 2004).

Devido à elevada sensibilidade e rapidez das análises, a fluorescência da clorofila *a* vem sendo amplamente empregada em estudos envolvendo estresses abióticos, permitindo identificar alterações fisiológicas antes mesmo da manifestação de sintomas visíveis (Kalaji *et al.*, 2016).

Dessa forma, essa técnica apresenta grande potencial para o monitoramento do estado fisiológico das plantas e para a avaliação da eficiência de estratégias mitigadoras voltadas à manutenção da atividade fotossintética sob condições adversas (Kalaji *et al.*, 2016).

2.4 Estresse oxidativo e metabolismo antioxidante

O metabolismo celular vegetal envolve continuamente processos de oxidação e redução essenciais para a manutenção do crescimento, desenvolvimento e produção de energia (Hura; Hura; Ostrowska, 2023). Durante condições ambientais favoráveis, existe equilíbrio entre a produção e a remoção de espécies reativas de oxigênio (ROS), permitindo o funcionamento adequado dos processos metabólicos (Hasanuzzaman *et al.*, 2020).

Entretanto, quando as plantas são expostas a condições de estresse, esse equilíbrio pode ser alterado, resultando no acúmulo excessivo dessas moléculas e desencadeando estresse oxidativo (Hasanuzzaman *et al.*, 2020).

As espécies reativas de oxigênio constituem moléculas altamente instáveis produzidas naturalmente durante processos metabólicos, principalmente nos cloroplastos, mitocôndrias e peroxissomos (Hasanuzzaman *et al.*, 2020). Entre as principais ROS produzidas em células vegetais destacam-se o radical superóxido (O_2^-), o peróxido de hidrogênio (H_2O_2), o oxigênio singleto ($^1O_2$) e o radical hidroxila (OH). Em concentrações moderadas, essas moléculas podem atuar como sinalizadores envolvidos em processos de crescimento, desenvolvimento e respostas adaptativas. No entanto, sua produção excessiva pode provocar danos celulares severos (Hasanuzzaman *et al.*, 2020).

Sob condições de déficit hídrico, a limitação na assimilação de CO_2 associada ao fechamento estomático reduz a utilização dos elétrons gerados durante a fase fotoquímica da fotossíntese. Como consequência, ocorre sobre-redução da cadeia transportadora de elétrons e aumento do fluxo de elétrons para rotas alternativas, favorecendo a formação excessiva de ROS (Mittler *et al.*, 2022; Hasanuzzaman *et al.*, 2020).

O acúmulo dessas moléculas pode promover danos oxidativos em diferentes componentes celulares. A peroxidação lipídica representa um dos principais efeitos do estresse oxidativo, comprometendo a integridade das membranas celulares e alterando sua permeabilidade (Hasanuzzaman *et al.*, 2020; Mittler *et al.*, 2022).

Além disso, proteínas podem sofrer oxidação e desnaturação, enquanto pigmentos fotossintéticos podem ser degradados, reduzindo a eficiência dos processos fotossintéticos. Alterações estruturais em ácidos nucleicos também podem ocorrer, comprometendo processos relacionados à expressão gênica e à divisão celular (Gill; Tuteja, 2010; Hasanuzzaman *et al.*, 2020; Mittler *et al.*, 2022).

Para minimizar os danos provocados pelo excesso de espécies reativas de oxigênio, as plantas desenvolveram sistemas antioxidantes altamente eficientes, compostos por mecanismos enzimáticos e não enzimáticos. Esses mecanismos atuam de forma integrada para controlar a produção e a remoção de ROS, contribuindo para a manutenção da homeostase celular (Hasanuzzaman *et al.*, 2020; Gill; Tuteja, 2010).

Entre os mecanismos antioxidantes enzimáticos, a superóxido dismutase (SOD) é considerada a primeira linha de defesa antioxidante (Zhang *et al.*, 2024). Essa enzima catalisa a conversão do radical superóxido em peróxido de hidrogênio e oxigênio molecular, reduzindo a toxicidade inicial causada pelo acúmulo de O_2^- (Zhang *et al.*, 2024). Entretanto, embora menos reativo que o radical superóxido, o H_2O_2 também pode provocar danos celulares caso não seja adequadamente removido (Zhang *et al.*, 2024; Hasanuzzaman *et al.*, 2020).

A remoção do peróxido de hidrogênio ocorre principalmente pela ação de enzimas como catalase (CAT) e ascorbato peroxidase (APX) (Mishra *et al.*, 2023). A catalase atua promovendo a decomposição direta do H_2O_2 em água e oxigênio, apresentando elevada capacidade catalítica principalmente em situações de elevada concentração desse composto (Mishra *et al.*, 2023; Hasanuzzaman *et al.*, 2020). Em contraste, a APX integra o ciclo ascorbato-glutationa e apresenta elevada afinidade pelo H_2O_2, atuando em concentrações mais baixas e permitindo um controle mais refinado da homeostase oxidativa (Nakano; Asada, 1981; Hasanuzzaman *et al.*, 2020).

Além dos mecanismos antioxidantes enzimáticos, plantas submetidas ao déficit hídrico frequentemente acumulam compostos osmoprotetores capazes de contribuir para a manutenção do equilíbrio osmótico e proteção celular (Kavi Kishor *et al.*, 2015).

Entre esses compostos, a prolina apresenta destaque devido à sua ampla participação em respostas ao estresse (Kavi Kishor *et al.*, 2015; Hasanuzzaman *et al.*, 2020).

A prolina atua como importante osmorregulador celular, contribuindo para a manutenção do potencial hídrico, estabilização de proteínas e membranas, proteção estrutural de enzimas e redução de danos oxidativos (Renzetti; Funck; Trovato, 2025). O aumento nos níveis desse aminoácido frequentemente é utilizado como indicador bioquímico de resposta ao estresse hídrico, refletindo mecanismos adaptativos relacionados à tolerância vegetal (Renzetti; Funck; Trovato, 2025).

Embora a ativação do sistema antioxidante represente importante estratégia de defesa, estudos recentes sugerem que mecanismos capazes de reduzir a geração inicial de espécies reativas de oxigênio podem apresentar maior eficiência na tolerância ao estresse quando comparados à ativação intensa dos sistemas de detoxificação (Mittler *et al.*, 2022; Kalaji *et al.*, 2016). Nesse contexto, estratégias capazes de preservar a funcionalidade do aparato fotossintético e otimizar o transporte de elétrons têm recebido crescente atenção, uma vez que podem reduzir a pressão oxidativa diretamente em sua origem (Sampaio-Filho *et al.*, 2026; Mittler *et al.*, 2022).

2.5 Silício como mitigador de estresses abióticos

Embora o silício (Si) não seja considerado um elemento essencial para a maioria das plantas superiores, diversos estudos têm demonstrado seu papel benéfico no crescimento vegetal e na tolerância a diferentes tipos de estresse abiótico e biótico (Epstein, 1999).

O interesse pela utilização desse elemento tem aumentado significativamente nas últimas décadas devido à sua capacidade de promover alterações estruturais, fisiológicas e bioquímicas capazes de melhorar o desempenho das plantas em condições ambientais adversas (Epstein, 1999; Coskun *et al.*, 2019).

O silício encontra-se naturalmente presente no solo principalmente na forma de silicatos minerais. Entretanto, sua absorção pelas plantas ocorre predominantemente na forma de ácido monossilícico [$Si(OH)_4$], sendo posteriormente transportado via xilema e distribuído para diferentes tecidos vegetais (Luyckx *et al.*, 2017). Após sua absorção, o Si pode ser depositado principalmente na parede celular, na cutícula e nos espaços intercelulares, promovendo alterações estruturais relacionadas à resistência mecânica dos tecidos (Luyckx *et al.*, 2017).

Além de atuar como componente estrutural, o silício apresenta importantes efeitos fisiológicos associados à manutenção do metabolismo vegetal. Estudos têm demonstrado que plantas suplementadas com Si frequentemente apresentam maior crescimento, maior área foliar,

aumento da biomassa e maior eficiência fotossintética, especialmente quando submetidas a condições de estresse (Coskun *et al.*, 2019; Xu; Guo; Liu, 2022).

Sob condições de déficit hídrico, diversos mecanismos têm sido propostos para explicar os efeitos benéficos do silício. Entre esses mecanismos destaca-se a manutenção do estado hídrico das plantas. O Si pode contribuir para a redução das perdas de água por transpiração devido ao aumento da deposição de sílica na epiderme e à formação de barreiras físicas que reduzem a transpiração excessiva. Além disso, esse elemento pode influenciar mecanismos relacionados à abertura estomática, favorecendo maior eficiência no uso da água (Coskun *et al.*, 2019; Luyckx *et al.*, 2017).

Outro mecanismo frequentemente relatado refere-se à preservação da atividade fotossintética. O déficit hídrico promove alterações no fluxo de elétrons e reduz a eficiência dos processos fotoquímicos, comprometendo a utilização adequada da energia absorvida. Diversos estudos demonstram que o fornecimento de silício pode preservar a integridade dos fotossistemas e favorecer a manutenção do transporte eletrônico durante condições de estresse (Zivcak *et al.*, 2014; Zhu; Gong, 2014).

Melhorias em parâmetros derivados da fluorescência da clorofila *a* têm sido observadas em plantas tratadas com silício, incluindo aumentos na eficiência de transporte eletrônico e redução da dissipação excessiva de energia (Kalaji *et al.*, 2016). Reduções em parâmetros associados ao fechamento dos centros de reação do PSII e aumentos na eficiência do fluxo eletrônico indicam maior estabilidade do aparato fotossintético e menor pressão de excitação sobre os centros fotoquímicos (Kalaji *et al.*, 2016; Chen *et al.*, 2016).

Além dos efeitos sobre a atividade fotossintética, o silício também tem sido associado à modulação do metabolismo antioxidante. A aplicação desse elemento pode reduzir o acúmulo excessivo de espécies reativas de oxigênio, diminuindo danos oxidativos causados pelo estresse hídrico. Diversos estudos relatam aumento na atividade de enzimas antioxidantes como SOD, CAT e APX em plantas tratadas com Si (Hasanuzzaman *et al.*, 2020; Xu; Guo; Liu, 2022).

Entretanto, resultados recentes sugerem que o efeito do silício sobre o metabolismo antioxidante pode não estar relacionado exclusivamente ao aumento da atividade enzimática. Em determinadas situações, reduções na atividade antioxidante em plantas tratadas com silício têm sido interpretadas como indicativas de menor pressão oxidativa, sugerindo que a manutenção da eficiência fotoquímica pode reduzir a geração inicial de ROS e, consequentemente, diminuir a necessidade de intensa ativação dos mecanismos antioxidantes (Mittler *et al.*, 2022; Sampaio-Filho *et al.*, 2026).

Além dos mecanismos fisiológicos e bioquímicos, o silício pode atuar na modulação da expressão gênica associada à resposta ao estresse. Alterações na expressão de genes relacionados ao transporte de água, à síntese de compostos antioxidantes e aos mecanismos de defesa têm sido observadas em diferentes espécies vegetais suplementadas com esse elemento (Coskun *et al.*, 2019).

Em cucurbitáceas, embora estudos ainda sejam relativamente limitados quando comparados a outras culturas, evidências recentes demonstram efeitos positivos do silício sobre o crescimento vegetal, a manutenção dos pigmentos fotossintéticos, a eficiência fotoquímica e a tolerância ao déficit hídrico. Entretanto, os mecanismos envolvidos nessas respostas ainda não são completamente compreendidos, especialmente quando o Si é utilizado em associação com outras estratégias mitigadoras (Saadaoui *et al.*, 2023; Xu; Guo; Liu, 2022).

Dessa forma, a utilização do silício apresenta elevado potencial como ferramenta para redução dos efeitos negativos provocados pelo déficit hídrico, particularmente em cenários de mudanças climáticas e crescente limitação dos recursos hídricos (IPCC, 2023; Mittler *et al.*, 2022).

2.6 Filmes de partículas à base de óxido de cálcio como estratégia mitigadora do déficit hídrico

O uso de tecnologias voltadas à redução dos efeitos negativos de estresses ambientais tem recebido crescente atenção na agricultura moderna, principalmente diante do aumento da frequência de eventos climáticos extremos e da necessidade de maior eficiência no uso dos recursos hídricos (IPCC, 2023). Entre essas estratégias, a utilização de filmes de partículas tem se destacado devido à capacidade de modificar o microambiente foliar e contribuir para a manutenção da atividade fisiológica das plantas sob condições adversas (IPCC, 2023; Glenn; Puterka, 2005.

Os filmes de partículas consistem na aplicação de compostos minerais finamente dispersos sobre a superfície foliar, formando uma camada protetora capaz de alterar propriedades ópticas e térmicas das folhas. Essa película pode atuar refletindo parte da radiação incidente, reduzindo a absorção excessiva de energia e minimizando danos associados à elevada temperatura foliar e à sobrecarga fotoquímica (Glenn; Puterka, 2005; Sharma; Vijay Rakesh Reddy; Datta, 2015).

Diversos materiais têm sido utilizados na formulação desses filmes, incluindo caulim, carbonato de cálcio, dióxido de silício e compostos à base de cálcio. Entre esses materiais, o óxido de cálcio (CaO) apresenta potencial promissor devido à combinação entre propriedades físicas relacionadas à refletância e possíveis efeitos fisiológicos associados ao cálcio (Glenn; Puterka, 2005; Oliveira *et al.*, 2021).

A aplicação de filmes de partículas à base de CaO pode modificar a distribuição da radiação absorvida pelas folhas, promovendo redução da temperatura foliar e contribuindo para maior equilíbrio entre absorção e utilização da energia luminosa. Sob condições de elevada irradiância e déficit hídrico, essa redução na carga energética pode minimizar a ocorrência de fotoinibição e preservar a integridade funcional do aparato fotossintético (Oliveira *et al.*, 2021; Oliveira Junior *et al.*, 2026).

A redução da temperatura foliar promovida por filmes de partículas pode apresentar efeitos adicionais relacionados ao balanço hídrico das plantas. Temperaturas mais elevadas aumentam a demanda evaporativa atmosférica, intensificando perdas de água por transpiração. Assim, ao reduzir o aquecimento excessivo da superfície foliar, os filmes podem contribuir para maior eficiência no uso da água e menor intensidade dos efeitos causados pela limitação hídrica (Glenn; Puterka, 2005; Oliveira Junior *et al.*, 2026).

Além dos efeitos físicos, o cálcio desempenha importantes funções estruturais e fisiológicas no metabolismo vegetal. Esse elemento participa da estabilização das membranas celulares e da parede celular, contribuindo para a manutenção da integridade estrutural dos tecidos vegetais. O cálcio também atua como importante mensageiro secundário em vias de sinalização celular associadas às respostas ao estresse (Thor, 2019; Dodd; Kudla; Sanders, 2010).

Mudanças nas concentrações intracelulares de cálcio podem ativar diferentes mecanismos relacionados à adaptação vegetal, incluindo regulação estomática, expressão gênica e ativação de proteínas quinases, fatores de transcrição e outras proteínas envolvidas em respostas adaptativas ao estresse. Dessa forma, além dos efeitos relacionados à proteção física das folhas, compostos contendo cálcio podem atuar diretamente em mecanismos fisiológicos associados à tolerância ao estresse (Thor, 2019; Dodd; Kudla; Sanders, 2010).

Diversos estudos têm demonstrado resultados positivos do uso de filmes de partículas em diferentes culturas agrícolas. Em cafeeiro, a aplicação de filmes de partículas contendo cálcio promoveu aumento da assimilação líquida de CO_2, maior eficiência no uso da água, redução da temperatura foliar e preservação da atividade fotoquímica (Silva *et al.*, 2019).

Resultados semelhantes foram posteriormente observados em batata-doce e videira, nos quais filmes à base de óxido de cálcio favoreceram a fotoproteção e o incremento da produtividade (Oliveira *et al.*, 2021; Oliveira Junior *et al.*, 2026).

A manutenção da eficiência fotoquímica representa um dos principais efeitos observados em plantas tratadas com filmes de partículas. Alterações em parâmetros de fluorescência da clorofila *a* têm indicado melhorias relacionadas à absorção e utilização da

energia luminosa, aumento da eficiência do transporte eletrônico e redução da dissipação excessiva de energia na forma de calor (Oliveira *et al.*, 2021; Kalaji *et al.*, 2016).

Entretanto, embora diversos estudos tenham demonstrado benefícios associados ao uso de filmes de partículas, a resposta das plantas pode variar em função da concentração aplicada. Concentrações inadequadas podem provocar efeitos negativos relacionados ao excesso de refletância e ao sombreamento excessivo da superfície foliar, reduzindo a quantidade de radiação disponível para os processos fotossintéticos (Glenn; Puterka, 2005; Oliveira *et al.*, 2021).

Assim, a definição de concentrações adequadas torna-se fator essencial para maximizar os efeitos positivos dessa tecnologia. O equilíbrio entre a redução da carga energética excessiva e a manutenção da absorção luminosa suficiente para a fotossíntese parece representar um aspecto central para a eficiência dos filmes de partículas à base de óxido de cálcio (Oliveira *et al.*, 2021).

Apesar dos resultados promissores observados em diferentes culturas, estudos envolvendo a utilização de filmes de partículas à base de CaO em abóbora 'Mini Jack' ainda são escassos, principalmente sob condições de déficit hídrico. Dessa forma, investigações relacionadas aos mecanismos ecofisiológicos associados à utilização dessa tecnologia podem contribuir para ampliar o entendimento sobre sua aplicação como estratégia mitigadora em sistemas agrícolas (Oliveira *et al.*, 2021; Oliveira Junior *et al.*, 2026).

2.7 Uso combinado de silício e óxido de cálcio: eficiência fotoquímica e metabolismo antioxidante

Estratégias voltadas à mitigação dos efeitos provocados pelo déficit hídrico têm evoluído progressivamente de abordagens isoladas para mecanismos integrados capazes de atuar simultaneamente em diferentes níveis fisiológicos. Entre essas estratégias, a associação entre silício (Si) e óxido de cálcio (CaO) surge como alternativa promissora devido ao potencial de atuação complementar desses compostos sobre processos relacionados à proteção estrutural, à manutenção da atividade fotossintética e à regulação do metabolismo antioxidante (Mittler *et al.*, 2022; Coskun *et al.*, 2019).

Os efeitos benéficos do silício e do cálcio sobre a tolerância vegetal ao estresse hídrico têm sido amplamente descritos individualmente. O silício apresenta capacidade de melhorar o estado hídrico das plantas, preservar a funcionalidade do aparato fotossintético e modular mecanismos antioxidantes. Por outro lado, o cálcio exerce funções relacionadas à integridade estrutural das células, à estabilidade das membranas e à sinalização celular, além dos efeitos físicos promovidos pelos filmes de partículas sobre a superfície foliar (Coskun *et al.*, 2019; Thor, 2019).

Apesar do conhecimento existente sobre os efeitos individuais desses compostos, ainda permanece limitada a compreensão dos mecanismos envolvidos quando ambos são utilizados em associação. A hipótese de ação conjunta fundamenta-se na possibilidade de atuação em diferentes etapas da resposta ao estresse, promovendo efeitos complementares e potencialmente sinérgicos (Coskun *et al.*, 2019; Oliveira Junior *et al.*, 2026).

Sob condições de déficit hídrico, o comprometimento do transporte de elétrons e a redução da assimilação de carbono promovem aumento da pressão de excitação sobre os centros fotoquímicos, favorecendo a geração excessiva de espécies reativas de oxigênio. Em muitos casos, a resposta vegetal depende predominantemente da ativação do sistema antioxidante para a remoção dessas moléculas após sua formação (Mittler *et al.*, 2022; Hasanuzzaman *et al.*, 2020).

Entretanto, mecanismos capazes de limitar a geração inicial de espécies reativas de oxigênio podem representar uma estratégia fisiológica mais eficiente, reduzindo a necessidade de elevada ativação dos sistemas antioxidantes. Nesse contexto, a associação entre silício e CaO pode contribuir para deslocar a resposta vegetal de uma estratégia predominantemente reativa para uma estratégia preventiva (Mittler *et al.*, 2022; Kalaji *et al.*, 2016).

Essa abordagem preventiva baseia-se na manutenção da funcionalidade do aparato fotossintético e na redução da sobrecarga energética antes do estabelecimento de danos oxidativos significativos. O filme de partículas à base de CaO pode reduzir a absorção excessiva de radiação e minimizar o aquecimento foliar, enquanto o silício pode contribuir para uma maior estabilidade estrutural dos fotossistemas e para a manutenção do fluxo eletrônico (Oliveira *et al.*, 2021; Coskun *et al.*, 2019).

Como consequência, melhorias na eficiência fotoquímica podem reduzir a pressão sobre os centros de reação do fotossistema II e diminuir o acúmulo de elétrons em componentes intermediários da cadeia transportadora. Alterações em parâmetros de fluorescência da clorofila *a*, como reduções em M0, VK e VJ e aumentos em ET0/TR0 e ET0/ABS, podem indicar maior eficiência no aproveitamento da energia absorvida e menor dissipação energética (Kalaji *et al.*, 2016; Strasser; Tsimilli-Michael; Srivastava, 2004).

A manutenção da eficiência fotoquímica pode também influenciar diretamente o balanço redox celular. Quando o transporte eletrônico ocorre de maneira eficiente, a probabilidade de transferência inadequada de elétrons para rotas alternativas diminui, reduzindo a formação excessiva de espécies reativas de oxigênio (Mittler *et al.*, 2022; Hasanuzzaman *et al.*, 2020).

Como consequência, a necessidade de intensa ativação das enzimas antioxidantes pode ser reduzida. Em determinadas situações, menores atividades de SOD, CAT e APX não necessariamente indicam redução da capacidade de defesa antioxidante, podendo representar menor pressão oxidativa sobre as células vegetais (Kalaji *et al.*, 2016).

Essa interpretação tem sido reforçada por estudos que relacionam a manutenção da funcionalidade do aparato fotossintético com a redução da geração primária de ROS, deslocando a resposta vegetal de uma estratégia predominantemente reativa para uma estratégia preventiva (Mittler *et al.*, 2022; Kalaji *et al.*, 2016). Dessa forma, a interpretação das respostas antioxidantes deve considerar sua associação com alterações no aparato fotossintético e não apenas os valores absolutos das atividades enzimáticas.

Além disso, respostas relacionadas ao acúmulo de compostos osmoprotetores também podem ser influenciadas pela melhoria do estado fisiológico das plantas. Menores concentrações de prolina em tratamentos mitigadores podem refletir uma redução na intensidade do estresse percebido pelas plantas, indicando maior equilíbrio metabólico (Kavi Kishor *et al.*, 2015; Hasanuzzaman *et al.*, 2020).

Apesar do potencial dessa abordagem integrada, estudos envolvendo a aplicação conjunta de silício e óxido de cálcio ainda permanecem escassos, particularmente em cucurbitáceas. Embora resultados positivos tenham sido observados com o uso isolado de filmes de partículas de CaO em cafeeiro, batata-doce e videira (Silva *et al.*, 2019; Oliveira *et al.*, 2021; Oliveira Junior *et al.*, 2026), os mecanismos ecofisiológicos decorrentes da associação entre Si e CaO ainda são pouco compreendidos.

Dessa forma, compreender como a associação entre silício e óxido de cálcio influencia simultaneamente a eficiência fotoquímica e a regulação do metabolismo antioxidante pode contribuir para o desenvolvimento de estratégias mais eficientes de manejo em condições de limitação hídrica, além de ampliar o entendimento sobre mecanismos fisiológicos relacionados à tolerância ao estresse (Mittler *et al.*, 2022; Coskun *et al.*, 2019).

2.8 Aprendizado de máquina aplicado à fisiologia vegetal e à predição da produtividade

A produtividade vegetal constitui uma característica complexa, resultante da interação entre fatores ambientais, condições edáficas, práticas de manejo e processos fisiológicos que atuam em diferentes escalas temporais e espaciais (Ansarifar; Wang; Archontoulis, 2021).

A disponibilidade hídrica, a temperatura, a radiação, as propriedades do solo e as intervenções agronômicas influenciam processos relacionados às relações hídricas, ao funcionamento fotossintético, ao crescimento e à alocação de fotoassimilados, cujos efeitos

acumulados contribuem para determinar o desempenho produtivo das culturas (Fahad *et al.*, 2017; Moore *et al.*, 2021).

Consequentemente, a predição da produtividade representa um problema complexo, uma vez que as relações entre os fatores envolvidos podem apresentar interações e comportamentos lineares e não lineares (Ansarifar; Wang; Archontoulis, 2021; Van Klompenburg; Kassahun; Catal, 2020).

O avanço das tecnologias de aquisição e armazenamento de dados tem ampliado a utilização de métodos de aprendizado de máquina (*machine learning* – ML) na agricultura (Van Klompenburg; Kassahun; Catal, 2020). Esses métodos permitem explorar grandes volumes de informações e identificar padrões associados ao crescimento, ao estado nutricional, à ocorrência de estresses e à produtividade das culturas (Benos *et al.*, 2021). Dados meteorológicos, propriedades do solo, práticas de manejo, informações fenotípicas e dados provenientes de sensores e imagens têm sido utilizados em diferentes combinações para o desenvolvimento de modelos preditivos (Van Klompenburg; Kassahun; Catal, 2020; Benos *et al.*, 2021). Estudos mostram que a predição de produtividade constitui uma das aplicações consolidadas do aprendizado de máquina na agricultura e envolve ampla diversidade de culturas, variáveis preditoras e estruturas algorítmicas (Van Klompenburg; Kassahun; Catal, 2020; Benos *et al.*, 2021).

A integração de diferentes fontes de informação tem adquirido importância na modelagem agrícola, pois cada grupo de variáveis representa componentes distintos do sistema produtivo (Pathak *et al.*, 2023). Variáveis ambientais caracterizam as condições às quais as plantas estão submetidas; informações de manejo representam intervenções capazes de modificar essas condições; indicadores fisiológicos descrevem respostas funcionais; e características biométricas representam a expressão acumulada do crescimento e do desenvolvimento (Pathak *et al.*, 2023; Shamsuddin *et al.*, 2024). Nesse sentido, a integração de dados ambientais, espectrais, fenotípicos e agronômicos pode ampliar a representação da variabilidade associada à produtividade (Pathak *et al.*, 2023). Entretanto, a melhor combinação de informações pode depender da cultura, do ambiente e do algoritmo utilizado, indicando que o simples aumento do número de variáveis não garante necessariamente uma melhor capacidade de predição (Pathak *et al.*, 2023; Shamsuddin *et al.*, 2024).

Essa questão está diretamente relacionada à seleção e à organização das variáveis preditoras (Abdel-Salam *et al.*, 2024). A presença de atributos redundantes, altamente correlacionados ou pouco informativos pode aumentar a complexidade do modelo sem necessariamente melhorar sua capacidade de generalização (Pudjihartono *et al.*, 2022). Por outro lado, a exclusão de variáveis fisiologicamente complementares pode reduzir a representação dos processos biológicos associados à variável resposta (Pathak *et al.*, 2023). Assim, a construção de modelos preditivos deve considerar não apenas a quantidade de atributos disponíveis, mas também sua relevância, redundância e complementaridade informacional (Van Klompenburg; Kassahun; Catal, 2020; Shawon *et al.*, 2024).

A capacidade de representar essas relações varia de acordo com a estrutura de aprendizagem de cada algoritmo (Goldblum *et al.*, 2024). A Regressão Linear estima a variável resposta a partir de uma combinação linear dos preditores, atribuindo coeficientes que expressam a direção e a magnitude de suas associações com a variável-alvo (Roustaei *et al.*, 2024). A simplicidade estrutural favorece a interpretação dos resultados, mas sua capacidade pode ser limitada quando a resposta depende de limiares, interações complexas ou relações curvilíneas (Hastie; Tibshirani; Friedman, 2009). Em sistemas agrícolas, a inclusão explícita de interações pode melhorar a representação da produtividade, demonstrando que a dependência entre os fatores constitui um componente relevante da modelagem (Ansarifar; Wang; Archontoulis, 2021).

O Random Forest, proposto por Breiman (2001), constitui um método de aprendizado conjunto baseado na construção de múltiplas árvores de decisão. Cada árvore é desenvolvida a partir de amostras aleatórias das observações e, em cada divisão dos nós, subconjuntos das

variáveis são avaliados. Em problemas de regressão, a estimativa final é obtida pela agregação das predições das árvores individuais. Essa estrutura permite representar relações não lineares, limiares e interações sem exigir a especificação prévia da forma funcional das relações entre os preditores e a variável resposta (Breiman, 2001).

A capacidade de modelar interações complexas tem favorecido a aplicação do Random Forest em diferentes problemas agrícolas. O algoritmo tem sido utilizado para predição de produtividade, estimativa de características biofísicas e integração de variáveis climáticas, edáficas e de manejo (Van Klompenburg; Kassahun; Catal, 2020; Benos *et al.*, 2021). Também tem sido empregado para estimar atributos fisiológicos, como o conteúdo de clorofila foliar, demonstrando sua capacidade de explorar conjuntos de preditores relacionados ao estado fisiológico vegetal (Shah *et al.*, 2019).

Além da capacidade preditiva, o Random Forest permite estimar a importância relativa dos atributos. Essa característica possibilita avaliar quais variáveis apresentam maior contribuição para as decisões realizadas pelo conjunto de árvores. Entretanto, a importância de uma variável não deve ser interpretada como sinônimo de seleção ou exclusão automática, uma vez que diferentes atributos podem participar das árvores com contribuições distintas. A interpretação da importância também exige cautela quando os preditores são fortemente correlacionados, condição frequente em dados fisiológicos provenientes de processos funcionalmente conectados (Breiman, 2001; Strobl *et al.*, 2008).

A Regressão por Vetores de Suporte (*Support Vector Regression* – SVR), implementada no WEKA por meio do SMOreg, apresenta uma estrutura de aprendizagem diferente. O método busca construir uma função de regressão que equilibre a complexidade do modelo e a magnitude dos erros de predição. O uso de funções *kernel* possibilita representar relações não lineares por meio da transformação implícita dos dados em espaços de maior dimensionalidade. Dessa forma, a SVR pode ser aplicada a problemas em que a relação entre os preditores e a variável resposta não é adequadamente representada por uma função linear simples (Smola; Schölkopf, 2004).

A escolha do algoritmo mais adequado depende da estrutura dos dados e do problema investigado. Revisões da literatura sobre predição agrícola demonstram que não existe um algoritmo universalmente superior em todas as culturas, escalas e conjuntos de preditores. O desempenho depende da quantidade e qualidade das observações, das variáveis utilizadas, do pré-processamento dos dados, da estratégia de validação e da complexidade das relações entre os atributos e a variável-alvo (Van Klompenburg; Kassahun; Catal, 2020; Benos *et al.*, 2021; Shawon *et al.*, 2024).

Apesar do avanço do aprendizado de máquina na agricultura, grande parte dos modelos de produtividade utiliza informações meteorológicas, edáficas ou derivadas de sensoriamento remoto (Van Klompenburg; Kassahun; Catal, 2020). A utilização direta de indicadores fisiológicos ainda constitui uma abordagem comparativamente menos frequente, embora apresente potencial para aproximar a modelagem dos processos biológicos responsáveis pelo crescimento e pela produção (Varghese *et al.*, 2023). Nesse contexto, a fluorescência da clorofila *a* constitui uma fonte de informação particularmente relevante, por permitir a avaliação rápida e não destrutiva do funcionamento do aparato fotossintético (Kalaji *et al.*, 2016).

O transiente OJIP e os parâmetros derivados do JIP-test permitem caracterizar processos relacionados à absorção de energia, ao aprisionamento da excitação, à atividade dos centros de reação, ao transporte de elétrons e à dissipação do excesso energético (Strasser; Tsimilli-Michael; Srivastava, 2004; Kalaji *et al.*, 2016). Embora expressos como parâmetros individuais, esses atributos representam diferentes componentes de uma mesma cadeia funcional. Assim, alterações em uma etapa do transporte eletrônico podem repercutir simultaneamente sobre diferentes parâmetros, resultando em elevada interdependência fisiológica (Strasser; Tsimilli-Michael; Srivastava, 2004; Kalaji *et al.*, 2016).

A estrutura multivariada dos dados de fluorescência apresenta potencial para aplicação de algoritmos capazes de explorar relações complexas. Estudos recentes têm demonstrado que informações derivadas da fluorescência podem ser empregadas não apenas para interpretação fisiológica convencional, mas também como variáveis de entrada em sistemas de classificação e predição. A utilização conjunta de múltiplos atributos pode capturar padrões que não seriam evidentes pela análise isolada de um único parâmetro (Xia *et al.*, 2022; Tran *et al.*, 2024).

A relação entre fluorescência da clorofila e produtividade foi investigada diretamente por Ding *et al.* (2022) em algodoeiro. Os autores avaliaram parâmetros de fluorescência de folhas superiores e utilizaram Regressão por Vetores de Suporte, rede neural BP e XGBoost para a predição da produtividade. Os resultados demonstraram a viabilidade do uso da fluorescência na estimativa do rendimento e mostraram que o desempenho depende da organização das informações utilizadas no modelo (Ding *et al.*, 2022).

Em escala distinta, Peng *et al.* (2020) avaliaram a contribuição da fluorescência da clorofila induzida pelo Sol, de índices de vegetação e de variáveis climáticas para a predição da produtividade agrícola. Foram comparados cinco algoritmos, demonstrando que o desempenho preditivo variou em função tanto do método quanto da fonte de informação incorporada ao modelo (Peng *et al.*, 2020). Embora a fluorescência induzida pelo Sol seja metodologicamente diferente do transiente OJIP, o estudo demonstra o valor de informações relacionadas à atividade fotossintética na modelagem da produtividade.

A utilização de fluorescência induzida pelo Sol também tem sido explorada em trigo com algoritmos como Random Forest e XGBoost, reforçando a incorporação crescente de indicadores relacionados à atividade fotossintética em modelos de rendimento (Joshi *et al.*, 2023). Esses avanços indicam que a representação direta ou indireta do funcionamento fotossintético pode fornecer informações complementares aos dados ambientais e agronômicos tradicionalmente empregados na predição.

Entretanto, a produtividade representa o resultado acumulado de processos que ocorrem ao longo do desenvolvimento vegetal e, portanto, não depende exclusivamente do estado fotoquímico registrado em um único momento. Os pigmentos fotossintéticos acrescentam informações sobre a composição do aparato de absorção da luz, enquanto as características biométricas representam respostas acumuladas do crescimento. Assim, a combinação entre parâmetros fotoquímicos, pigmentares e biométricos pode representar diferentes escalas temporais e níveis de organização da resposta vegetal (Wahab *et al.*, 2022; Qiao *et al.*, 2024).

A inclusão das variáveis de manejo amplia essa representação, pois acrescenta fatores capazes de induzir ou modular as respostas fisiológicas. A disponibilidade hídrica interfere diretamente no funcionamento fotossintético e no crescimento, enquanto estratégias de manejo destinadas à mitigação do estresse podem modificar as condições às quais a planta está submetida (Wahab *et al.*, 2022; Qiao *et al.*, 2024). Consequentemente, a integração entre manejo, parâmetros OJIP, pigmentos e características biométricas permite representar desde os fatores associados à origem e à modulação do estresse até as respostas fisiológicas e as consequências acumuladas sobre o crescimento e a produtividade (Pathak *et al.*, 2023).

O desempenho relativo dos algoritmos pode, portanto, modificar-se conforme a estrutura informacional do conjunto de preditores. Estudos multimodais indicam que a combinação de fontes de dados e o algoritmo utilizado são fatores interdependentes, e a configuração de melhor desempenho pode variar entre culturas, regiões e escalas de análise (Pathak *et al.*, 2023). A literatura de predição agrícola também mostra que a combinação entre sensoriamento remoto, clima e outras fontes pode modificar substancialmente a capacidade dos modelos (Pathak *et al.*, 2023).

Nesse contexto, a integração entre ecofisiologia vegetal e aprendizado de máquina apresenta potencial para ampliar tanto a capacidade de predição quanto a compreensão das relações entre o funcionamento fisiológico e a produtividade. A literatura demonstra avanços no uso de ML para a estimativa do rendimento das culturas (Van Klompenburg; Kassahun; Catal, 2020), na aplicação de técnicas de aprendizado de máquina à análise de processos

fotossintéticos (Varghese *et al.*, 2023) e na utilização da fluorescência da clorofila como fonte de informação para modelos de produtividade (Ding *et al.*, 2022).

Entretanto, observa-se que ainda são limitados os estudos que integram progressivamente parâmetros detalhados do JIP-test, pigmentos fotossintéticos, características biométricas e variáveis de manejo para avaliar como diferentes níveis de informação biológica influenciam o desempenho de algoritmos com distintas estruturas de aprendizagem. Essa abordagem pode contribuir não apenas para a comparação da capacidade preditiva dos modelos, mas também para a compreensão de como a natureza fisiológica e agronômica das variáveis utilizadas no treinamento influencia a representação da produtividade.

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4. ARTIGO 1
CaO INFLUENCES THE YIELD AND FRUIT QUALITY OF 'MINI JACK' PUMPKIN UNDER DIFFERENT WATER REGIMES

Artigo formatado de acordo com as normas do periódico Agricultural Research

ABSTRACT

Water supply limitations may compromise plant development, the efficiency of the photosynthetic system, and pumpkin production. The use of CaO particle film has been adopted to mitigate the effects caused by drought stress. In this context, this study aimed to evaluate the impact of CaO particle film on the yield and fruit quality of Mini Jack pumpkin under full irrigation and drought stress conditions. CaO particle films were applied at four concentrations (0%, 2.5%, 5%, and 7.5%) to the leaves of pumpkin plants. The experiment was carried out in the field using a randomized block design. Chlorophyll a and b contents, chlorophyll a fluorescence, estimated fruit yield, and fruit quality were assessed. The treatment with 5% CaO, under both full irrigation and drought stress, resulted in increased average fruit weight and higher chlorophyll b content. Chlorophyll fluorescence parameters such as RE0/ABS, ET0/ABS, and TR0/DI0 indicated that the 5% CaO concentration enhanced the use of absorbed energy and improved electron transport efficiency, minimizing energy losses and strengthening the photosynthetic process. In contrast, lower (2.5%) and higher (7.5%) CaO concentrations did not promote improvements in plant performance. At 7.5% CaO, reductions in photosynthetic efficiency and fruit yield were observed, likely due to increased leaf shading and increased energy dissipation as heat. Therefore, the use of 5% CaO is an effective strategy for mitigating the negative effects of drought stress in Mini Jack pumpkin. The 5% CaO concentration favored an optimal balance between light absorption and efficient electron transport, resulting in higher fruit yield and quality even under limited water availability.

Keywords: *Cucurbitaceae*, ecophysiological parameters, water-use efficiency, stress mitigator.

4.1. Introduction

'Mini Jack' pumpkin (family *Cucurbitaceae*) is widely used worldwide, either due to its versatile applications or its easy development under tropical, subtropical, and summer conditions [22, 25, 2].

However, pumpkin is sensitive to abiotic stress conditions, including drought stress. Studies conducted with the crop have demonstrated that increasing drought stress can severely affect its ecophysiology and yield, also reducing leaf area, chlorophyll *a* and *b* contents, net photosynthetic rate, and carbohydrate levels, among other attributes [3, 18]. Low water availability also disrupts electron production and transport [19, 24].

In this regard, with ongoing climate change and the urgent need to meet global food demand, developing technologies to mitigate the damage caused by drought stress and to understand plant responses to this restriction becomes essential for improving crop performance [23]. One alternative to enhance plant protection against damage caused by drought stress is the use of calcium oxide (CaO)-based particle film.

The application of particle films has been recognized for reducing leaf damage and contributing to the maintenance of structural and chemical leaf composition, increasing photosynthetic efficiency [6, 9, 13, 20, 34], which consequently reflects on crop productivity [20].

In addition, particle films have high potential due to their low capacity to cause environmental damage, since their formulation consists of inert mineral particles that act as a

protective layer on leaves [29]. The effect of calcium oxide has been evaluated in several crops. In sweet potato, CaO increased productivity under ideal irrigation conditions [21]. In Conilon coffee plants, CaO-based film improved CO_2 assimilation rate, maintained transpiration, promoted water-use efficiency, and preserved the photochemical apparatus [11].

In tangerines, treatments with calcium particle films reduced plant temperature and decreased sunburn damage on fruits. Furthermore, in apple trees, reductions in photosynthetically active radiation and ultraviolet (UV) radiation were observed [16, 32].

For 'Mini Jack' pumpkin, no information is yet available regarding the impacts of CaO use under full irrigation and drought stress conditions. Considering the benefits provided by calcium particle films and the environmental challenges that hinder proper pumpkin development, the objective of this study was to evaluate the effect of calcium oxide particle film applied at different concentrations and under two water regimes and how these treatments may influence the ecophysiological performance, yield, and fruit quality of 'Mini Jack' pumpkin.

4.2. Material and Methods

4.2.1. Experiment site

The experiment was carried out at the Experimental Farm (10°55′27″ S; 37°12′01″ W; altitude 46 m). The region has a mean annual temperature of approximately 25.2°C, a dry summer, and mean annual precipitation of 1,300 mm concentrated between April and September, according to Köppen classification [27]. The soil in the area is classified as an Argissolo, a red-yellow Ultisol typical of Brazilian plains [26].

4.2.2. Plant material and experimental layout

'Mini Jack' pumpkin seeds were obtained from a commercial company, then sown and grown in 64-cell plastic trays filled with commercial substrate. Seedlings were irrigated daily, and 15 days after germination, they were transplanted to the field beds, which measured 18 m × 1.2 m, with spacing of 1.0 m × 0.80 m between plants. The crop was grown during the dry season, and the cycle lasted approximately 100 days. The experimental layout followed a randomized block design with three blocks per treatment, including border plants.

4.2.3. Crop management

After field establishment, plants received four CaO particle film concentrations: 0% (control), 2.5%, 5%, and 7.5%. The film was prepared in distilled water using a CaO suspension formulated on a weight-per-volume basis (w/v) and applied using a backpack electric sprayer (Kawashima PEM–P20) with a flow rate of 2.9 L min^{-1} and pressure of 450 kPa, ensuring uniform plant coverage. The particle film had a reflectance of approximately 90%, with particle size $\leq$ 2 μm [20]. Reapplications were performed weekly, maintaining constant *L values (lightness) [11].

Irrigation supply was estimated using the Penman–Monteith method based on reference evapotranspiration (ETo) [1]. At each phenological stage, crop evapotranspiration (ETc) was estimated from ETo and crop coefficient (Kc). Meteorological data were obtained from an A-409 automatic weather station (Instituto Nacional de Meteorologia – INMET).

4.2.4. Ecophysiological analyses

4.2.4.1. Falker Chlorophyll Index

Falker Chlorophyll Index (FCI) measurements were taken for chlorophyll *a* (Chl *a*) and chlorophyll *b* (Chl *b*); total chlorophyll (Chl *a* + Chl *b*) and the chlorophyll *a*/*b* ratio (Chl *a*/Chl *b*) were subsequently calculated. Measurements were performed using a ClorofiLOG device, which enables nondestructive assessment of the Falker chlorophyll index (Model CFL1030;

Falker, Brazil). This evaluation was based on absorbance of light emitted by diodes at three wavelengths: 635 and 660 nm (red) and 880 nm (infrared) [4, 8, 28].

4.2.4.2. Transient chlorophyll a fluorescence

Transient chlorophyll *a* fluorescence was measured using a fluorometer (Model OS-30p, Opti-Sciences Inc., USA). Evaluations were performed at 9:00 a.m. on healthy leaves located in the middle third of the plant. Initially, leaves were dark-adapted using specific clips for 30 min, and an actinic light pulse (λ = 660 nm) was applied uniformly for 1 s to a 4-mm diameter leaf area. Subsequently, transient states were induced by maximum illumination of 3,000 µmol m^{-2} s^{-1} (photons) [12, 11, 20].

The assessment allowed rapid determination of the fluorescence kinetics from initial (F0) to maximum (Fm). The following stages of the OJIP curve were defined: O ≅ F0 (50 µs), J (2 ms), I (30 ms), and P ≅ Fm. The time to maximum fluorescence emission t(Fm) and the area above the OJIP curve (A) were also determined. Based on OJIP curve results, the biophysical parameters ABS/CS, TR0/CS, ET0/CS, RE0/CS, DI0/CS, RE0/ABS, ET0/ABS, TR0/ABS, TR0/DI0, DI0/ABS, M0, VK, and VJ were estimated using equations for the JIP test [31, 10, 30].

4.2.5. Yield and initial fruit quality

From the total fruits per treatment, six were randomly sampled and evaluated for biometric traits (horizontal and longitudinal diameter) using a digital caliper (mm). Yield was estimated based on fruit production per plant using a digital scale, and results were expressed in grams (g).

4.2.6. Fruit firmness

Fruit pulp firmness was determined using a digital penetrometer (TR Turoni, Model 53205, Forli, Italy) with a 3-mm diameter tip, through measurements taken at three different points in the equatorial region of each fruit, expressed in Newtons (N).

4.2.7. Total soluble solids and total titratable acidity

Fruit samples from each treatment were analyzed for total soluble solids (TSS) expressed in °Brix using a digital refractometer (Model RTD-45, Instrutherm). The fruit pulp extract was then titrated with 0.01 N NaOH, according to AOAC (2002), to determine total titratable acidity (TTA), expressed as a percentage of citric acid.

4.2.8. Statistical analysis

Data were analyzed using Shapiro–Wilk and Bartlett tests; means were compared using Tukey's test (5%) with the RBio software package [5]. Graphs were plotted using SigmaPlot 12.5 (Systat Software, San Jose, CA, USA).

4.3. Results

Fruit yield per 'Mini Jack' pumpkin plant (g) was significantly affected by the treatments under optimal irrigation conditions. The control produced fruits with an average weight of 156.2 g. Plants treated with 5% CaO differed statistically from the control, showing a fruit weight increase of 22.4 g, resulting in an average of 178.6 g per fruit. Higher CaO concentrations negatively affected fruit production per plant; when subjected to 7.5% CaO, fruit weight decreased by 28.9 g compared with the best-performing concentration, 5% CaO (Fig. 1, a).

Under drought stress, 5% CaO differed statistically from the other treatments and resulted in the highest averages compared with the control and 7.5% CaO. Plants treated with 5% CaO produced fruits with an average weight of 149.1 g, while the control and 7.5% CaO

treatments yielded fruits with average weights of 138.7 g and 129.9 g, respectively, representing declines of 10.4 g and 19.2 g per fruit (Fig. 1, b).

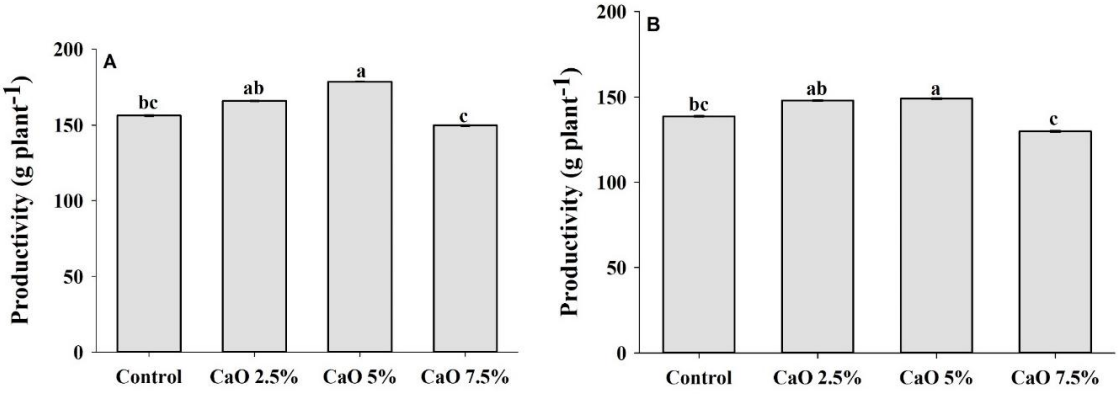

Fig 1. 'Mini Jack' pumpkin yield under different CaO concentrations in optimal irrigation conditions (A) and under drought stress (B). Means followed by the same letter do not differ from each other according to Tukey's test ($p < 0.05$).

Under ideal irrigation conditions, chlorophyll *b* content differed statistically among treatments. The 7.5% CaO treatment resulted in significant increases in chlorophyll *b* of 17.4% and 12% relative to the control and 2.5% CaO treatments, respectively. However, chlorophyll *b* content did not differ statistically between plants treated with 5% and 7.5% CaO. No statistical difference was detected in chlorophyll *a* content among treatments under the same water conditions (Fig. 2, a).

Under drought stress, chlorophyll b content also differed statistically among treatments. Plants treated with 5% CaO had the highest averages for this pigment, with increases of 8.99% and 12.97% compared with the control and 7.5% CaO, respectively. Chlorophyll b content did not differ statistically between plants treated with 2.5% and 5% CaO. However, no statistical differences were observed among treatments for chlorophyll a content (Fig. 2, b).

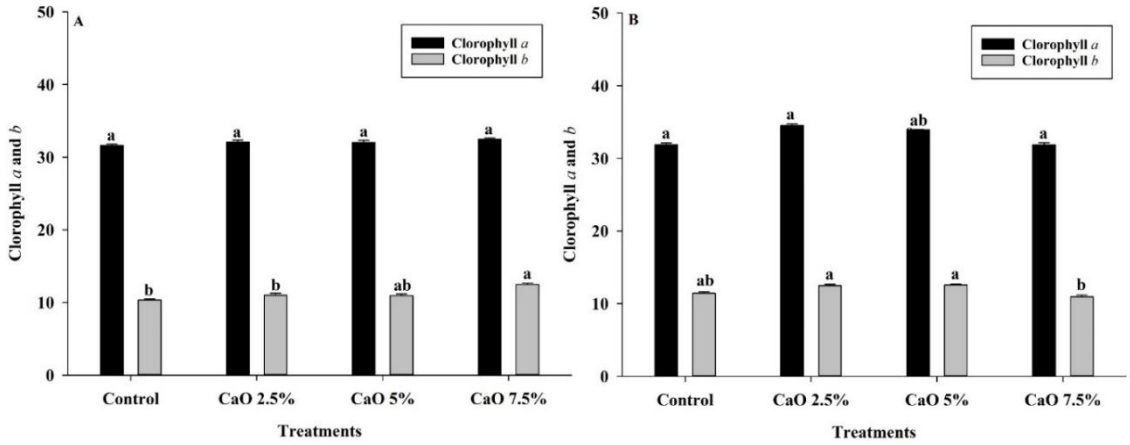

Fig 2. Falker chlorophyll *a* and chlorophyll *b* indices in 'Mini Jack' pumpkin plants under different CaO concentrations in optimal water conditions (100% ETo) (A) and under drought stress (66% ETo) (B). Means followed by the same letter do not differ according to Tukey's test ($p < 0.05$).

Treatments influenced the behavior of the OKJIP fluorescence transient curve of chlorophyll *a* (Fig. 3). Compared with the other treatments, 5% CaO resulted in the lowest fluorescence values at points O, K, J, and I and promoted an increase at the I–P step (Fig. 3, a).

The use of 5% CaO films also decreased VK and VJ, differing from the other treatments (Fig. 3, b).

Under drought stress, plants treated with 5% CaO showed lower fluorescence values at points O, K, J, and I compared with the control and 2.5% CaO treatments, and higher values than those under 7.5% CaO at the I–P step of the curve (Fig. 3, c). Additionally, plants treated with 5% CaO exhibited reductions in VK and VJ, differing from the other treatments and suggesting lower excitation pressure on photosystem II (Fig. 3, d).

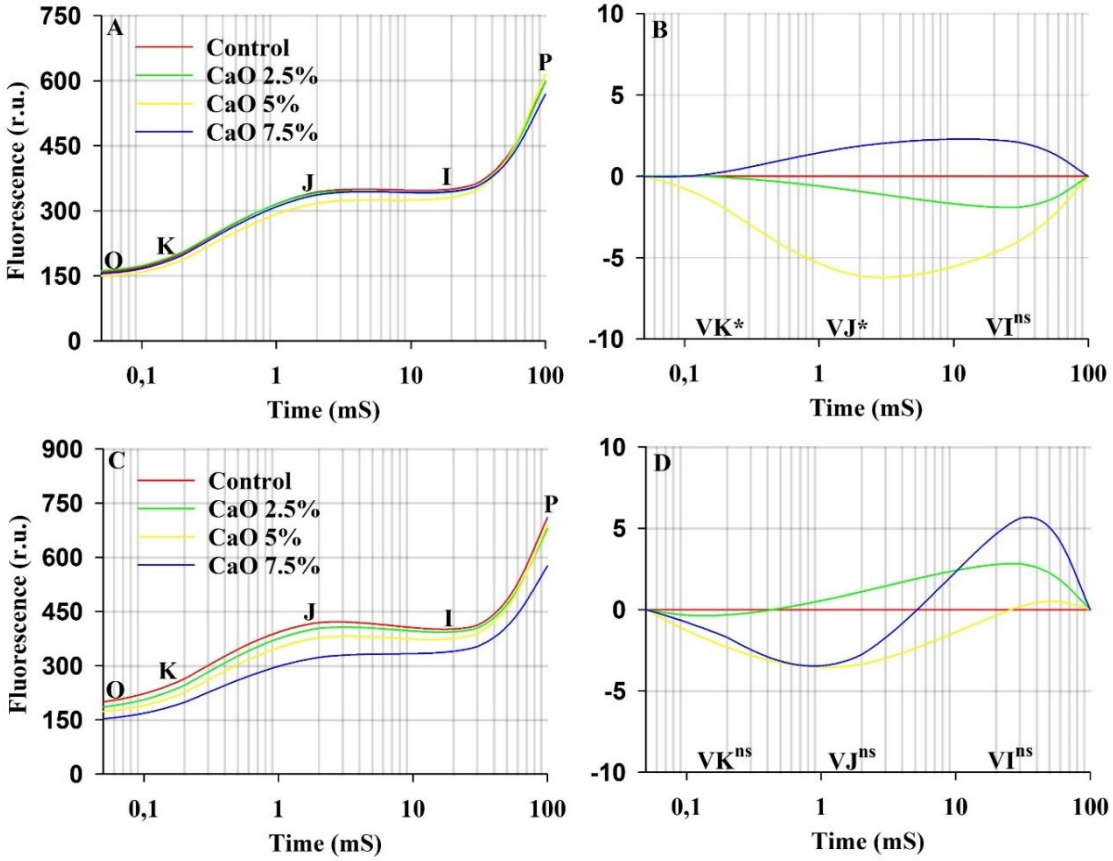

Fig 3. OKJIP transient chlorophyll *a* fluorescence curves and relative variable fluorescence at points K (VK), J (VJ), and I (VI) (B) in 'Mini Jack' pumpkin plants treated with different calcium oxide (CaO) concentrations under full irrigation (A and B) and drought stress conditions (C and D).

Pumpkin plants treated with 5% CaO under optimal water conditions showed improvements in photosystem II cross-section parameters, including electron trapping (TR0/CS), electron transport (ET0/CS), and the flux of electrons from quinone A (QA) to the final PSI acceptors per cross-section (RE0/CS). Under drought stress, the treatments caused significant variations in plant fluorescence parameters. The results demonstrated that applying 5% CaO provided a positive balance among different photosynthetic fluorescence components (ABS/CS, TR0/CS, ET0/CS, RE0/CS, and DI_0/CS). Energy absorption efficiency (ABS/CS) varied significantly among treatments, with the control showing the highest value (19.96), whereas 7.5% CaO had the lowest value (15.3). In percentage terms, CaO at 2.5%, 5%, and 7.5% resulted in reductions of 7%, 13%, and 23% in absorption efficiency, respectively, compared with the control. (Fig. 4).

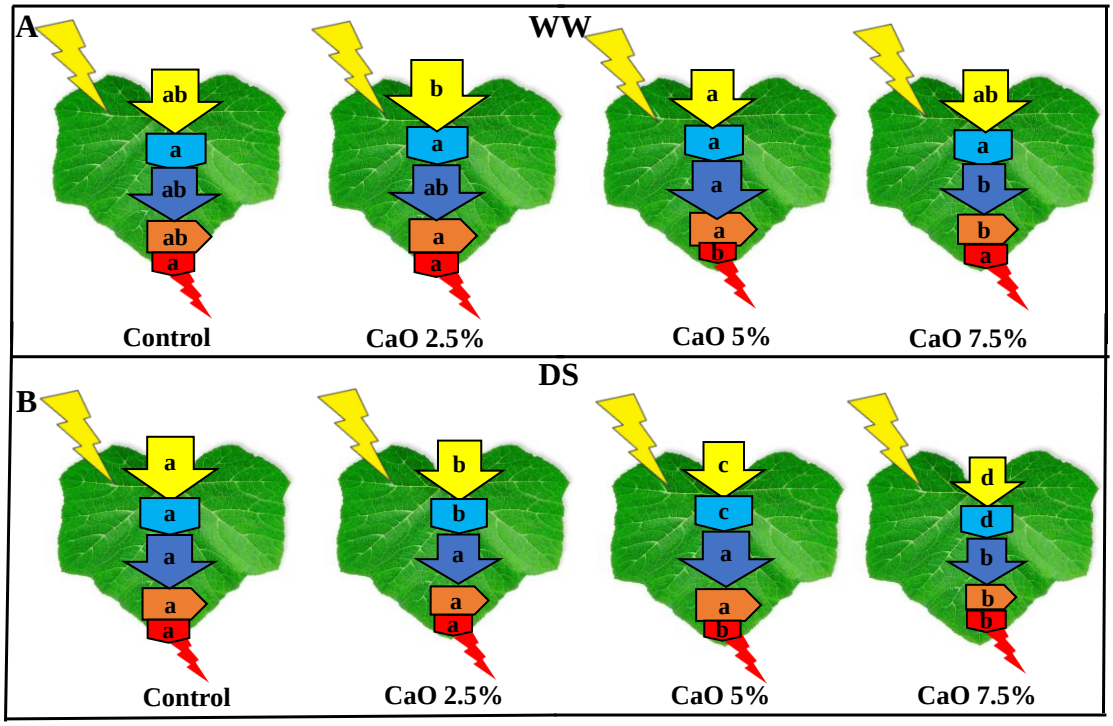

Fig 4. Leaf model of phenomenological energy fluxes per excited cross-section in 'Mini Jack' pumpkin plants treated with different concentrations of calcium oxide (0%, 2.5%, 5%, and 7.5%) under two water regimes: well-watered (WW) and drought-stress (DS). Arrow width corresponds to flux intensity. Yellow arrow – ABS/CS; blue arrow – TR0/CS; navy arrow – ET0/CS; brown arrow – RE0/CS; red arrow – DI0/CS. Means followed by the same letter do not differ according to Tukey's test ($p < 0.05$).

Energy trapping efficiency (TR0/CS) also indicated higher values in control plants, while those treated with 7.5% CaO exhibited the lowest value. Relative to the control, 2.5% CaO reduced TR0/CS by 6%, whereas 5% and 7.5% CaO reduced it by 10% and 22%, respectively. For energy transfer efficiency (ET0/CS), no significant differences were observed among the control, 2.5% CaO, and 5% CaO treatments, which showed ET0/CS values of 8.17, 7.53, and 7.82, respectively. However, plants treated with 7.5% CaO showed a significantly lower value (6.70), corresponding to an 18% reduction relative to the control. Energy recovery efficiency (RE0/CS) remained high for the control, 2.5% CaO, and 5% CaO treatments (83.85, 75.03, and 75.56, respectively). In contrast, 7.5% CaO caused a significant reduction of 29% relative to the control.

Analysis of the DI0/CS parameter, which represents non-productive energy dissipation, indicated decreasing values with higher CaO concentrations. Plants treated with 5% CaO (43.76) and 7.5% CaO (40.72) exhibited lower values compared with the control (56.21). In percentage terms, 5% CaO reduced non-productive energy dissipation by 22%, whereas 7.5% CaO reduced it by 27% relative to the control (Fig. 4).

The use of different CaO concentrations in 'Mini Jack' pumpkin plants grown under ideal irrigation affected chlorophyll *a* fluorescence parameters (Fig. 5, a). The 5% CaO treatment resulted in superior plant performance among the tested treatments, with high values of RE0/ABS, ET0/ABS, TR0/ABS, and TR0/DI0, indicating greater efficiency in electron transport and in the reduction step of the electron transport chain. These results demonstrate a balance between energy capture and energy use, with lower dissipation as heat, evidenced by DI0/ABS.

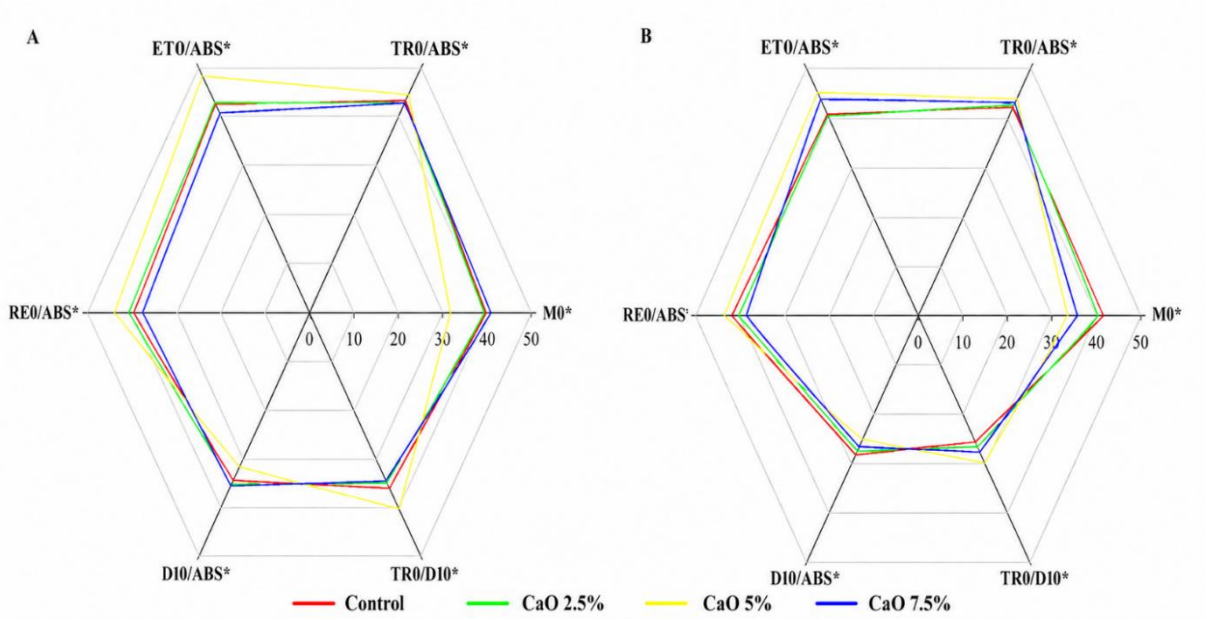

Fig 5. Radar chart of transient chlorophyll *a* fluorescence parameters in 'Mini Jack' pumpkin plants under different CaO concentrations in well-watered conditions (100% ETo) (A) and under drought stress (66% ETo) (B). Parameter abbreviations and their biological meanings are described in the abbreviations list. * Indicates statistical significance according to the F-test ($p < 0.05$).

Plants treated with 2.5% and 5% CaO under drought stress showed improvement in fluorescence parameters. However, 5% CaO exhibited higher values of ET0/ABS and RE0/ABS, indicating greater efficiency in electron transport and utilization. Furthermore, under drought stress, the 5% CaO treatment maintained a desirable relationship between energy trapping and dissipation (TR0/DI0) (Fig. 5, b). In contrast, the control and 7.5% CaO treatments resulted in higher energy dissipation, evidenced by increased DI0/ABS, indicating greater heat loss (Fig. 5, b).

Under full irrigation (100% ETo), the application of CaO particle films significantly affected the initial pH and titratable acidity (TTA) of 'Mini Jack' pumpkin fruits. Fruits from control plants exhibited the highest pH (7.58 ± 0.04), whereas the application of 5% and 7.5% CaO resulted in lower values of 7.42 ± 0.07 and 7.36 ± 0.04, respectively. These two concentrations differed significantly from the control but did not differ from each other. The 2.5% CaO treatment produced an intermediate pH value (7.48 ± 0.06) and did not differ significantly from either the control or the higher CaO concentrations. A similar statistical response was observed for TTA, expressed as a percentage of citric acid. The control fruits showed the highest TTA value (1.605 ± 0.00%), while fruits treated with 5% and 7.5% CaO exhibited values of 1.391 ± 0.09% and 1.1235 ± 0.10%, respectively, both differing significantly from the control. The 2.5% CaO treatment showed an intermediate value of 1.177 ± 0.09% and did not differ from the other treatments. Despite the numerical variation among treatments, no significant differences were detected for fruit width (44.61–48.32 mm), length (76.47–78.69 mm), total soluble solids (5.53–6.20 °Brix), maturation index (3.86–5.33), or firmness (11.32–13.51). Therefore, under full irrigation, the initial postharvest response to CaO particle films was restricted to changes in fruit pH and titratable acidity (Table 1).

Table 1: Variables related to initial postharvest quality of 'Mini Jack' pumpkin fruits grown under full irrigation (100% ETo) and treated with CaO at the following concentrations: 0%, 2.5%, 5%, and 7.5%. TSS, TTA and MI refer, respectively, to total soluble solids, titratable

acidity expressed as a percentage of citric acid and maturation index. Means followed by the same letter do not differ according to Tukey's test ($p < 0.05$).

Treatments	Width (mm)	Length (mm)	TSS	pH	TTA	MI	Firmness
Control	44.61 ± 0.13a	76.93 ± 0.44a	6.2 ± 0.07a	7.58 ± 0.04a	1.605 ± 0.00a	3.86 ± 0.05a	12.77 ± 0.29a
CaO 2.5%	46.59 ± 0.38a	77.99 ± 0.31a	6.2 ± 0.09a	7.48 ± 0.06ab	1.177 ± 0.09ab	5.33 ± 0.20a	13.27 ± 0.13a
CaO 5%	48.32 ± 0.18a	78.69 ± 0.47a	6.13 ± 0.10a	7.42 ± 0.07b	1.391 ± 0.09b	4.44 ± 0.16a	13.51 ± 0.39a
CaO 7.5%	46.57 ± 0.48a	76.47 ± 0.12a	5.53 ± 0.19a	7.36 ± 0.04b	1.1235 ± 0.10b	5.06 ± 0.28a	11.32 ± 0.22a

Under drought stress (66% ETo), CaO treatments also affected postharvest quality variables (Table 2). Plants treated with 5% CaO showed the lowest TSS and titratable acidity values while maintaining the highest maturation index. In contrast, fruits from the 7.5% CaO treatment exhibited reduced fruit length and intermediate values for acidity and TSS.

Table 2: Variables related to initial postharvest quality of 'Mini Jack' pumpkin fruits under drought stress (66% ETo) and treated with CaO at the following concentrations: 0%, 2.5%, 5%, and 7.5%. TSS, TTA and MI refer, respectively, to total soluble solids, titratable acidity expressed as a percentage of citric acid, and maturation index. Means followed by the same letter do not differ according to Tukey's test ($p < 0.05$).

Treatments	Width (mm)	Length (mm)	TSS	pH	TTA	MI	Firmness
Control	42.28 ± 0.27a	72.99 ± 0.29ab	6.325 ± 0.08a	7.87 ± 0.08a	1.66 ± 0.07a	3.82 ± 0.09b	12.93 ± 0.52a
CaO 2.5%	43.01 ± 0.51a	74.75 ± 0.39a	6.23 ± 0.10a	7.70 ± 0.09a	1.56 ± 0.14a	4.12 ± 0.24ab	13.62 ± 0.25a
CaO 5%	44.03 ± 0.37a	76.06 ± 0.12a	5.13 ± 0.23b	7.51 ± 0.05b	0.86 ± 0.10b	6.08 ± 0.25a	9.67 ± 0.41a
CaO 7.5%	42.76 ± 0.35a	70.83 ± 0.20b	5.97 ± 0.17ab	7.74 ± 0.03a	1.28 ± 0.13ab	4.80 ± 0.27ab	14.02 ± 0,32a

4.4 Discussion

Crop productivity in general may be affected by drought stress, including in species adapted to regions with irregular rainfall or low water availability. In pumpkin, drought stress strongly affects photosynthetic capacity and consequently leads to yield decline [18].

However, the yield increase derived from higher fruit weight in plants treated with 5% CaO, both under full irrigation and under drought stress, indicates the important role played by the use of a calcium particle film for this crop. According to [21], a similar behavior was observed in sweet potato, in which the application of 10% and 15% CaO was able to mitigate the effects caused by adverse production conditions and increased crop yield.

In addition to reduced fruit yield, one of the effects triggered by adverse environmental conditions, including drought stress, is chlorophyll degradation [14]. In this study, it was observed that intermediate CaO concentrations (5%) under drought stress promoted an increase in Chl *b*. This result may be attributed to the conditions imposed on the plants, since low-light conditions lead to increased Chl *b* production. The increase in photosynthetic pigments plays a fundamental role in the efficiency of converting light energy into chemical energy [35], which can be observed through the parameters of transient chlorophyll *a* fluorescence.

Chlorophyll fluorescence is a highly important tool to assess and quantify the different reactions involved in the photosynthetic process. In this study, the application of 5% CaO promoted a significant optimization in fluorescence emission, evidenced by lower fluorescence values at the O, K, J, and I steps, both under full irrigation and under drought stress. The reduction at the initial steps of the O–K and J curves suggests a decrease in energy accumulation in the antenna complexes, indicating greater efficiency in dissipating excess absorbed energy and greater stability of the thylakoid membrane.

In addition, increased fluorescence at the I–P step in plants treated with 5% CaO suggests that this concentration favored the efficiency of electron transport, especially in the phase between photosystem II (PSII) and photosystem I (PSI). These results are consistent with studies by [30], which highlight the role of calcium oxide particle films in stabilizing the photosynthetic system under different environmental conditions.

Furthermore, the decrease in VK and VJ observed for the 5% CaO treatment, both under optimal and drought stress conditions, suggests a lower rate of energy loss as heat, resulting in greater efficiency in converting light energy into chemical energy. The reduction in VK indicates that the PSII reaction center is less subject to oxidative stress, whereas the decrease in VJ points to lower limitation of electron flow in the transport chain, particularly in the reduction of quinone A (QA) [7, 15].

Taken together, these effects reinforce the hypothesis that the use of 5% CaO films stabilizes the photosynthetic apparatus, possibly by reducing non-photochemical dissipation and optimizing the use of absorbed energy for electron transport and subsequent biochemical reactions.

The application of CaO promoted a reduction in photosynthetically active radiation in the light-harvesting complexes of induced chloroplasts, probably due to reduced energy absorption and fluorescence emission in the energy flow [30, 13]. Thus, the use of 5% CaO films prevents oxidative stress in ‘Mini Jack’ pumpkin plants under drought stress by reducing energy loss in the form of fluorescence.

The results obtained from the treatments indicate a positive influence on energy flux at the 5% CaO concentration, apparently by promoting an optimal balance between light energy absorption and electron transfer efficiency within PSII. The beneficial effect of 5% CaO under both optimal and drought stress conditions was also evident in the fluorescence parameters RE0/ABS, ET0/ABS, TR0/ABS, TR0/DI0 and DI0/ABS. These results indicate that the absorbed light energy is being concentrated, converted, and effectively used for electron transport in the photosynthetic processes, improving the plant’s carbon assimilation capacity.

Under drought stress conditions, the results confirm that the use of a 5% CaO film provides the best performance of ‘Mini Jack’ pumpkin plants among the treatments tested. When 5% CaO films are used, light absorption, electron transport and trapping in PSII, and the number of electrons reaching plastoquinone (PQ) (RE0/ABS, ET0/ABS and TR0/ABS) occur more efficiently [33], demonstrating that even under drought stress, plants treated with 5% CaO maintain high efficiency in the use of light energy.

The parameters DI0/ABS and TR0/DI0 are related to how the energy absorbed by the plant is used and dissipated and can be used to indicate plants under stress conditions [17]. Plants treated with 5% CaO showed the highest TR0/DI0 values and the lowest DI0/ABS values, indicating that the photosynthetic system is functioning efficiently and that most of the absorbed energy is used for photosynthesis rather than being lost as heat, thereby maximizing photosynthetic efficiency [30, 17].

4.5 Conclusions

The use of a 5% calcium oxide (CaO)-based particle film proved to be an efficient strategy to optimize ecophysiological performance, increase productivity, and preserve fruit quality in 'Mini Jack' pumpkin, both under optimal irrigation and under drought stress. The application of CaO films favors the stability and integrity of the photosynthetic apparatus, increasing Chl *b* content, improving fluorescence parameters such as RE0/ABS, ET0/ABS and TR0/DI0, and reducing energy losses (DI0/ABS). These effects resulted in higher average fruit weight and maintenance of relevant quality attributes, such as firmness, balanced pH, and titratable acidity. Based on the ecophysiological and yield responses, the 5% CaO film provides greater protection and improves agronomic performance in 'Mini Jack' pumpkin plants and can be used as an alternative under drought stress conditions.

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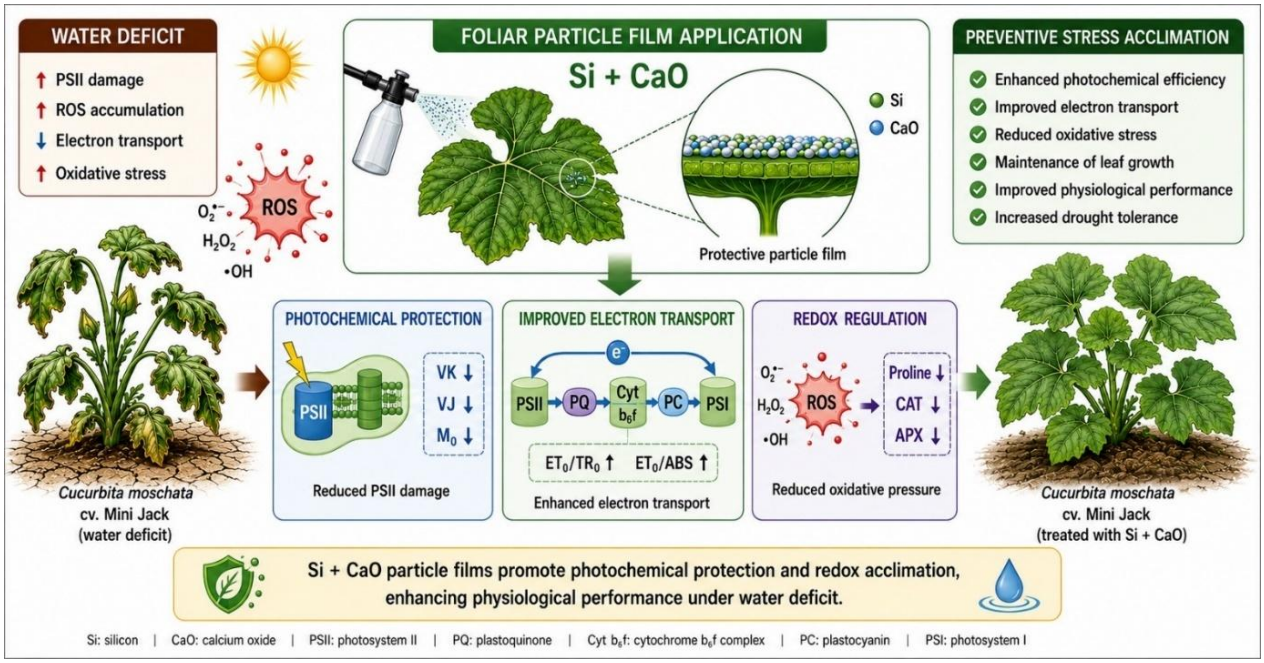
5. ARTIGO 2
SILICON AND CALCIUM OXIDE PARTICLE FILMS ENHANCE BIOCHEMICAL AND PHYSIOLOGICAL RESPONSES OF 'MINI JACK' PUMPKIN UNDER WATER DEFICIT

Artigo formatado de acordo com as normas do periódico Journal of the Science of Food and Agriculture

Abstract: Water-deficit stress is one of the major environmental constraints limiting agricultural productivity by impairing photosynthetic performance and disrupting cellular redox homeostasis. This study evaluated the effects of silicon- and calcium oxide-based particle films, applied individually or in combination, on the physiological and biochemical responses of 'Mini Jack' pumpkin plants under water-deficit conditions. The experiment was conducted under greenhouse conditions using a randomized complete block design arranged in a 2 × 4 factorial scheme, consisting of two irrigation regimes [well-watered (80% field capacity) and water-deficit (40% field capacity)] and four foliar treatments [control, silicon (Si), calcium oxide (CaO), and silicon + calcium oxide (Si + CaO)]. Water deficit reduced plant growth and induced Stress-related physiological and biochemical alterations. However, the combined application of Si and CaO increased chlorophyll content, the chlorophyll a/b ratio, and improved chlorophyll a fluorescence responses. OJIP analysis revealed lower VK and VJ values, higher ET0/TR0 and ET0/ABS ratios, and reduced M0, indicating improved electron transport performance and lower photochemical disturbance under stress conditions. In addition, particle film treatments reduced proline accumulation and modulated antioxidant enzyme activities (SOD, CAT, and APX), particularly under water-deficit conditions. The combined application of Si and CaO was associated with enhanced photochemical regulation and lower activation of stress-related biochemical responses, supporting the hypothesis that integrated modulation of photosynthetic performance and redox metabolism contributes to improved acclimation to water-deficit conditions.

Keywords: *Cucurbita moschata* Duchesne, water-deficit stress, chlorophyll fluorescence, plant protection, photochemical efficiency.

Graphical abstract:



5.1. Introduction

Water deficit stress is among the most important environmental constraints limiting plant productivity, impairing key physiological processes such as photosynthesis, electron transport, and cellular redox balance. Water restriction promotes over-reduction of the photosynthetic electron transport chain, thereby enhancing the generation of reactive oxygen species (ROS) and leading to oxidative stress, with direct consequences for photochemical efficiency and plant growth [1,2.]

In this context, tolerance to water-deficit largely depends on the ability of plants to preserve the functionality of the photosynthetic apparatus and maintain redox homeostasis. Traditionally, this regulation has been associated with the activation of antioxidant defense systems, which detoxify ROS and minimize oxidative damage. However, mechanisms that limit ROS production at its source, through the modulation of photochemical efficiency and electron transport dynamics, are increasingly recognized as effective strategies for stress tolerance[3].

The application of particle films and beneficial elements has been explored as a promising approach to mitigate the adverse effects of abiotic stresses. Calcium-based compounds may contribute to leaf surface protection and the maintenance of tissue integrity, whereas silicon has been associated with stabilization of the photosynthetic apparatus and modulation of antioxidant metabolism[4,5]. Although these effects have been extensively documented when applied individually, it remains unclear whether their combined application can induce synergistic effects on photochemical regulation and redox balance under water-deficit conditions. Furthermore, ecophysiological studies involving the 'Mini Jack' pumpkin cultivar remain scarce, with recent investigations focusing mainly on fruit growth, development, and physiological changes during maturation[6].

Based on these considerations, we hypothesized that the combined application of silicon and calcium oxide may not simply intensify known physiological responses, but instead promote a shift in the plant stress response strategy, from a predominantly reactive mechanism based on antioxidant activation to a preventive mechanism driven by reduced ROS generation through enhanced photochemical efficiency.

Therefore, this study aimed to evaluate the effects of isolated and combined applications of silicon and calcium oxide on ecophysiological and biochemical responses, with emphasis on the interaction between photochemical efficiency and antioxidant metabolism in 'Mini Jack' pumpkin plants under water-deficit conditions.

5.2. Material and Methods

5.2.1. Experimental area

The experiment was conducted in a greenhouse at the Experimental Farm of the Rural Campus of the Federal University of Sergipe, São Cristóvão, Sergipe, Brazil (10°55′46.1″ S; 37°06′14.7″ W), from June to August 2024. The regional climate is classified as tropical rainy, with an average annual temperature of approximately 25.2 °C[7].

The soil used in the experiment was classified as a Red-Yellow Ultisol, typical of Brazilian coastal plains[7,8]. After collection, the soil was sieved and transferred into 21L pots containing 20 kg of soil per experimental unit. Liming (1,000 kg ha^{-1} limestone, PRNT 90%) and fertilization were performed according to soil analysis and regional recommendations[9]. Nutrient supply was applied through nutrient solution at 7 and 15 days after emergence (DAE). Three 'Mini Jack' pumpkin seeds were sown per pot, and thinning was performed at 5 DAE, maintaining one plant per experimental unit.

5.2.2. Experimental design and treatments

The experiment was conducted using a randomized complete block design arranged in a 2 × 4 factorial scheme, consisting of two irrigation regimes: well-watered (80% of field

capacity) and water-deficit (40% of field capacity), combined with four foliar treatments: control, silicon (Si), calcium oxide (CaO), and silicon + calcium oxide (Si + CaO). This resulted in eight treatment combinations, with six replicates per treatment, totaling 48 experimental units. Each experimental unit consisted of one pot containing a single 'Mini Jack' pumpkin plant.

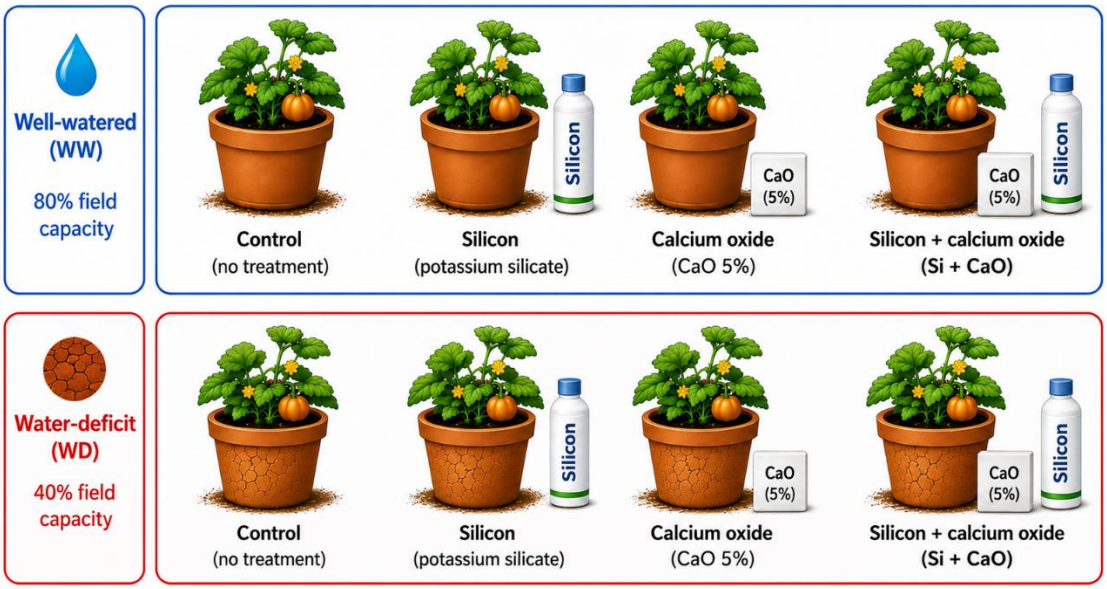


Fig. 1. Experimental design of 'Mini Jack' pumpkin plants under two irrigation regimes and four foliar treatments. Plants were subjected to well-watered conditions (WW; 80% field capacity) or water-deficit conditions (WD; 40% field capacity), combined with four foliar treatments: control (without treatment), calcium oxide (CaO; 5%), silicon (applied as potassium silicate), and silicon + calcium oxide (Si + CaO), resulting in eight treatment combinations.

Soil moisture was monitored daily using the gravimetric method (weighing method). Initially, pots were maintained at field capacity, and the corresponding pot weight was used to establish moisture levels equivalent to 80% field capacity for well-watered plants and 40% field capacity for water-deficit plants. Water replacement was performed daily to maintain the established moisture levels.

Silicon was applied at a rate of 0.4 L 100 L^{-1} (12% Si and 15% K), whereas CaO was applied at a concentration of 5%. Foliar applications were carried out at 15 days after sowing by manual spraying, either individually (Si or CaO) or in combination (Si + CaO), until complete leaf coverage was achieved, applying a total volume of 10 mL $plant^{-1}$. Standardized procedures were adopted to ensure uniform coverage and prevent runoff of Si and CaO onto the soil surface.

5.2.3. Ecophysiological evaluations

Ecophysiological evaluations were performed between 11:00 and 13:00 h on fully expanded leaves collected from the middle third of the plants.

5.2.3.1. Chlorophyll *a* transient fluorescence (OJIP)

Chlorophyll *a* transient fluorescence was measured after dark adaptation for 30 min using a portable fluorometer (OS-30p, Opti-Sciences, USA). Measurements were performed under a saturating light pulse of 3,000 µmol photons m^{-2} s^{-1}, with actinic light applied for 1 s over a uniformly illuminated leaf area of 4 mm diameter[10].

Rapid fluorescence kinetics from minimum fluorescence (F0) to maximum fluorescence (Fm) were recorded according to the OJIP transient curve, considering the characteristic fluorescence steps O (50 µs), K (200 µs), J (2 ms), I (30 ms), and P (maximum fluorescence

intensity). Based on OJIP data, the biophysical parameters ET0/CS0, ET0/ABS, ET0/TR0, and M0 were calculated according to the equations [11,12,13].

5.2.3.2. Chlorophyll indices

Chlorophyll *a* and *b* indices were determined non-destructively using a portable chlorophyll meter (CFL1030, Falker, Brazil), based on absorbance measurements at red and near-infrared wavelengths. The device provides absorbance readings that allow estimation of chlorophyll *a* and *b* pools [14, 15, 16].

5.2.4. Morphoagronomic parameters

Plant length (cm) and leaf area (LA) were evaluated. Leaf area was estimated from the width of fully expanded leaves and expressed as cm² according to a previously validated empirical model proposed by Silva et al. (2015), using the following equation:

$$LA = -83.63 - 51.112L + 111.378\sqrt{L} + 9.8047L^{1.5}$$

where:
LA = leaf area (cm²)
L = leaf width (cm)

5.2.5. Proline determination

Proline content was determined according to the method described by Bates[17]. Fresh tissue samples (0.1 g) were extracted in 3% sulfosalicylic acid and reacted with acid ninhydrin. Absorbance was measured at 520 nm, and results were expressed as μmol g^{-1} fresh mass (FM), based on a standard proline calibration curve (0, 0.05, 0.10, 0.15, and 0.20 μmol).

5.2.6. Antioxidant enzyme activity

5.2.6.1. Sample preparation

Enzyme extraction was performed using 0.2 g of fresh tissue macerated in liquid nitrogen and homogenized in potassium phosphate buffer (100 mM, pH 7.8) containing EDTA and ascorbic acid. The extract was centrifuged at 13,000 × *g* for 10 min at 4 °C, and the supernatant was collected and used for subsequent analyses.

5.2.6.2. Superoxide dismutase (SOD) activity

SOD activity was determined according to the method described by Beauchamp and Fridovich [18] with adaptations for microplate analysis. Aliquots of 10 μL enzyme extract were pipetted in triplicate into 96-well microplates, followed by the addition of 190 μL reaction buffer containing 50 mM potassium phosphate buffer (pH 7.8), 14 mM L-methionine, 0.1 mM EDTA, 75 μM nitroblue tetrazolium (NBT), and 2 μM riboflavin.

Plates were maintained in darkness prior to light exposure for 7 min. Absorbance was measured at 560 nm using a microplate reader (Epoch-BioTek®). Results were expressed as SOD units mg^{-1} fresh mass (FM).

5.2.6.3. Ascorbate peroxidase (APX) activity

APX activity was determined according to Nakano and Asada [19], with modifications. Aliquots of 9 μL diluted enzyme extract (1:2) were pipetted in triplicate into microplates, followed by the addition of 162 μL reaction buffer containing 100 mM potassium phosphate buffer (pH 7.0) and 0.5 mM ascorbic acid. The reaction was initiated by adding 9 μL hydrogen peroxide (2 mM).

Absorbance was recorded at 290 nm every 15 s for 3 min using a microplate reader (Epoch BioTek®). Results were expressed as APX units min^{-1} mg^{-1} FM.

5.2.6.4. Catalase (CAT) activity

CAT activity was determined according to Chance and Maehly[20], with modifications. Aliquots of 9 µL diluted enzyme extract (1:2) were pipetted in triplicate into microplates containing 162 µL potassium phosphate buffer (100 mM, pH 7.0). The reaction was initiated by adding 9 µL hydrogen peroxide (250 mM).

Hydrogen peroxide decomposition was monitored through the decrease in absorbance at 240 nm, with readings recorded every 15 s for 3 min using a microplate reader (Epoch BioTek®). Results were expressed as CAT units min^{-1} mg^{-1} FM.

5.2.7. Statistical analysis

Data were initially tested for normality using the Shapiro–Wilk test and subsequently subjected to two-way analysis of variance (ANOVA), considering irrigation regime and foliar treatment as fixed factors and blocks as a random factor. Significant effects were identified using the F-test ($p < 0.05$), and mean comparisons were performed using Tukey's test at the 5% probability level. Statistical analyses were conducted using the RBio package in R software (Bhering, 2017). Graphs were generated using SigmaPlot version 14.0 (Systat Software Inc., San Jose, CA, USA).

5.3. Results

5.3.1. Chlorophyll *a* transient fluorescence (OJIP)

Treatments affected chlorophyll *a* transient fluorescence kinetics under both irrigation conditions (Fig. 2 and Fig. 3). Under well-watered conditions, Si-treated plants showed lower fluorescence intensity at the O, K, and J steps and higher values at the I and P steps compared with the control treatment (Fig. 2A). Reductions in VK and VJ were also observed in Si and Si + CaO treatments, whereas VI did not differ among treatments.

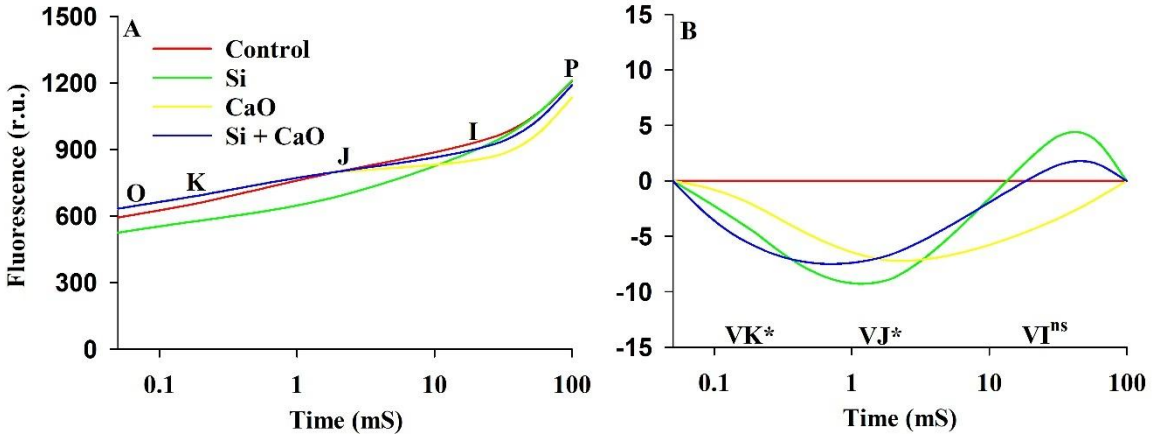


Fig. 2. Chlorophyll *a* transient fluorescence OJIP curve (A) and relative variable fluorescence at the K (VK), J (VJ), and I (VI) steps (B) in 'Mini Jack' pumpkin plants under well-watered conditions (WW) treated with silicon (Si; applied as potassium silicate), calcium oxide (CaO), and silicon + calcium oxide (Si + CaO).

Under water-deficit conditions, treatment effects became more pronounced (Fig. 3). Plants receiving the combined application of Si + CaO exhibited lower fluorescence intensity at the O, K, J, and I steps than the other treatments (Fig. 3A). This treatment also reduced VK and VJ values.

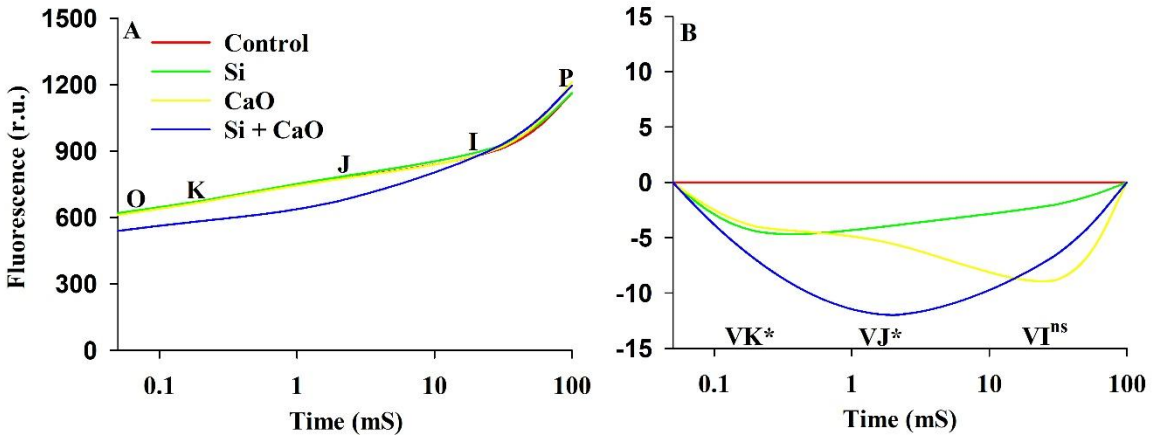


Fig. 3. Chlorophyll *a* transient fluorescence OJIP curve (A) and relative variable fluorescence at the K (VK), J (VJ), and I (VI) steps (B) in 'Mini Jack' pumpkin plants under water-deficit conditions (WD) treated with silicon (Si; applied as potassium silicate), calcium oxide (CaO), and silicon + calcium oxide (Si + CaO).

Derived fluorescence parameters were significantly affected by treatments (Fig. 4). Under well-watered conditions, all particle film treatments increased ET0/TR0, ET0/ABS, and ET0/CS0 and reduced M0 compared with the control treatment (Fig. 4A). Under water-deficit conditions, plants treated with Si + CaO showed higher ET0/TR0 and ET0/ABS values and lower M0 values, whereas ET0/CS0 did not differ among treatments.

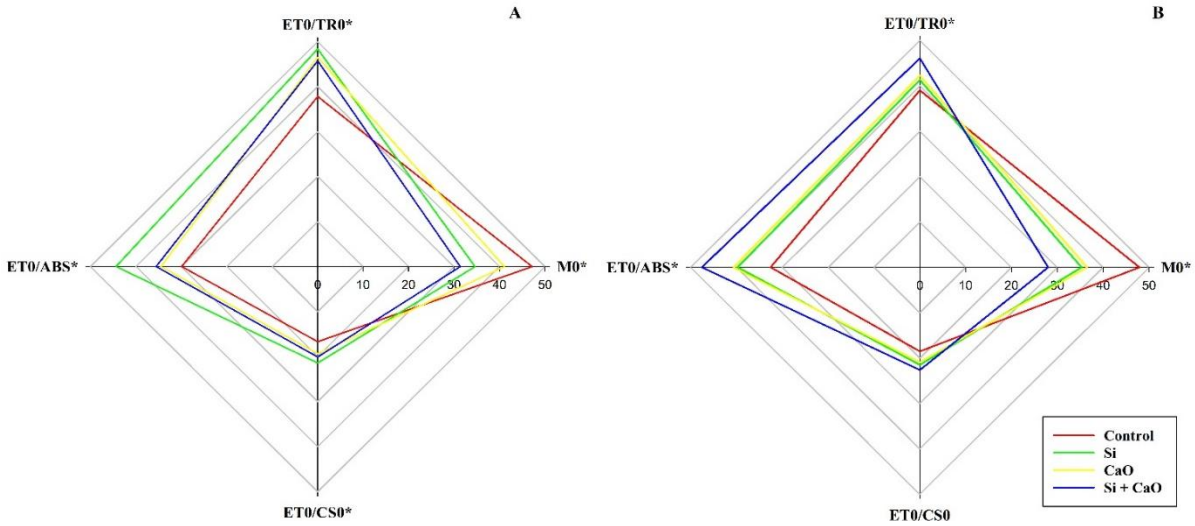


Fig. 4. Radar plots of chlorophyll *a* transient fluorescence parameters in 'Mini Jack' pumpkin plants under well-watered conditions (WW) (A) and water-deficit conditions (WD) (B) treated with silicon (Si; applied as potassium silicate), calcium oxide (CaO), and silicon + calcium oxide (Si + CaO). Parameter abbreviations and their biological meanings are described in the abbreviations section. * indicates significant differences according to the F-test ($p < 0.05$).

5.3.2. Chlorophyll indices

For chlorophyll *a*, a significant treatment effect was observed ($p < 0.05$), whereas irrigation regime and interaction effects were not significant. The Si + CaO treatment showed the highest chlorophyll *a* index (24.47), compared with the control (19.64), CaO (19.94), and Si (20.82) treatments (Fig. 5A).

Chlorophyll *b* was significantly affected by both treatments and irrigation regime ($p < 0.05$), without interaction effects. Plants treated with Si + CaO showed the highest chlorophyll *b* values (6.30), differing from the control treatment (5.63), while Si (5.91) and CaO (5.91) presented intermediate values (Fig. 5A). In addition, plants under well-watered conditions exhibited higher chlorophyll *b* content (6.07) compared with water-deficit conditions (5.80).

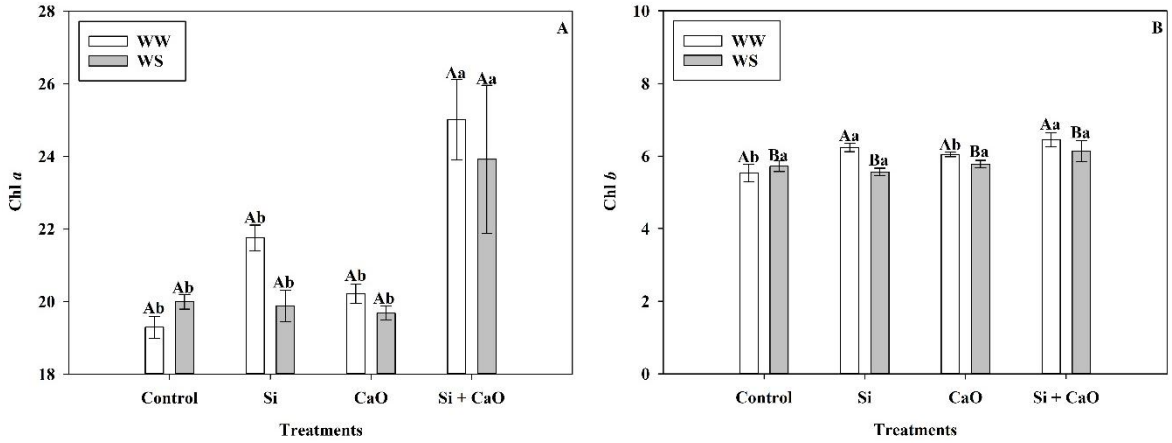


Fig. 5. Chlorophyll *a* (A) and chlorophyll *b* (B) Falker indices in 'Mini Jack' pumpkin plants subjected to well-watered conditions (WW) and water-deficit conditions (WD) and treated with silicon (Si; applied as potassium silicate), calcium oxide (CaO), and silicon + calcium oxide (Si + CaO). Means followed by the same uppercase letter (between irrigation regimes) and lowercase letter (among treatments within each irrigation regime) do not differ according to Tukey's test ($p \leq 0.05$). Error bars represent the standard error of the mean.

The chlorophyll *a/b* ratio and total chlorophyll content were significantly influenced by treatments ($p < 0.05$), with no significant effect of irrigation regime. The combined Si + CaO treatment showed the highest chlorophyll *a/b* ratio (3.90) and total chlorophyll content (30.77), differing from the other treatments.

5.3.3. Morphoagronomic parameters

Leaf area was significantly affected by irrigation regime, treatments, and their interaction ($p < 0.05$) (Fig. 6A). Silicon (1272.65 cm²) and calcium oxide (1437.42 cm²) treatments resulted in greater leaf area than the control (873.85 cm²) and Si + CaO (768.40 cm²) treatments.

Under well-watered conditions, Si-treated plants showed lower leaf area values (1157.02 cm²), whereas control (1626.10 cm²), CaO (1644.52 cm²), and Si + CaO (1468.92 cm²) treatments did not differ significantly.

Under water-deficit conditions, the reduction in leaf area was more pronounced in control plants, whereas plants treated with CaO showed smaller variations between irrigation conditions (Fig. 6A).

For plant length, only irrigation regime had a significant effect ($p < 0.05$), whereas treatment and interaction effects were not significant. Plants grown under well-watered conditions showed greater plant length (123.66 cm) than plants under water-deficit conditions (86.66 cm).

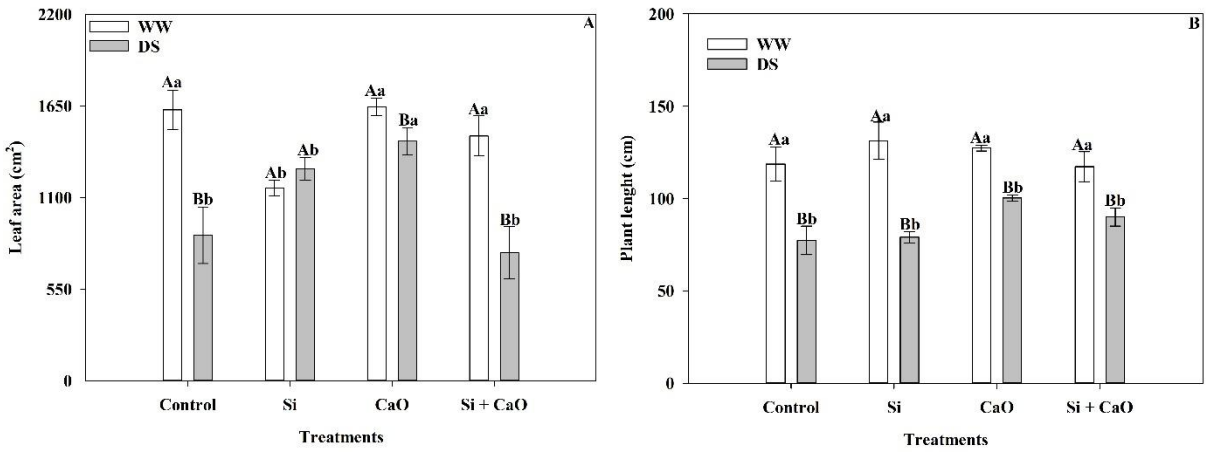


Fig. 6. Leaf area (A) (cm²) and plant length (B) (cm) of 'Mini Jack' pumpkin plants subjected to well-watered conditions (WW) and water-deficit conditions (WD) and treated with control, silicon (Si), calcium oxide (CaO), and silicon + calcium oxide (Si + CaO). Means followed by the same uppercase letter (between irrigation regimes) and lowercase letter (among treatments within each irrigation regime) do not differ according to Tukey's test ($p \leq 0.05$). Error bars represent the standard error of the mean.

5.3.4. Proline content and antioxidant enzyme activity

Proline content was significantly affected by irrigation regime, treatments, and their interaction ($p < 0.05$) (Fig. 7A). Under water-deficit conditions, control plants exhibited the highest proline content (4.08), differing from Si (1.14), Si + CaO (1.39), and CaO (1.90) treatments, which did not differ among themselves. Under well-watered conditions, no significant differences among treatments were observed.

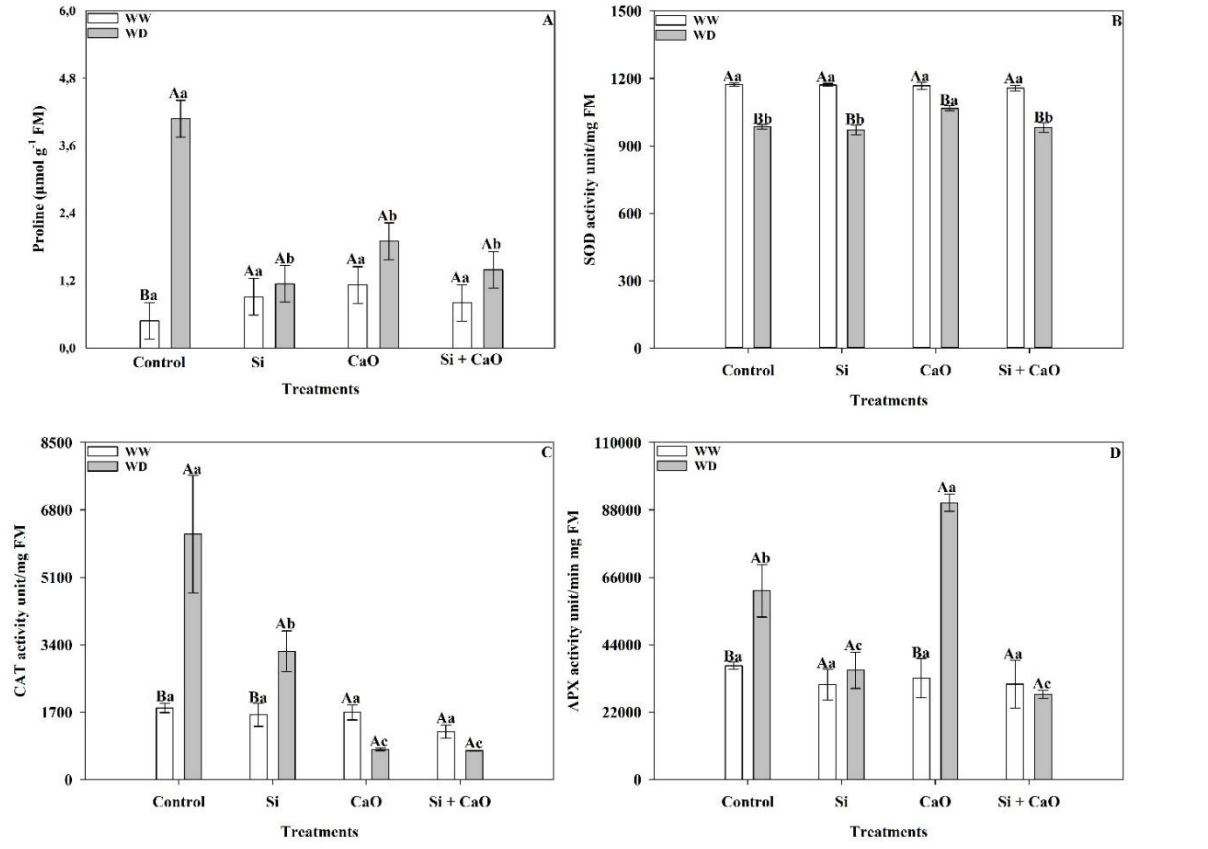


Fig. 7. Proline content (A), superoxide dismutase activity (SOD) (B), catalase activity (CAT) (C), and ascorbate peroxidase activity (APX) (D) in 'Mini Jack' pumpkin plants subjected to well-watered conditions (WW) and water-deficit conditions (WD) and treated with control, silicon (Si), calcium oxide (CaO), and silicon + calcium oxide (Si + CaO). Means followed by the same uppercase letter (between irrigation regimes) and lowercase letter (among treatments within each irrigation regime) do not differ according to Tukey's test ($p \leq 0.05$). Error bars represent the standard error of the mean.

The activity of antioxidant enzymes was significantly affected by irrigation regime, treatments, and their interaction ($p < 0.05$).

For SOD activity, under water-deficit conditions, CaO-treated plants showed the highest activity (1067.20), differing from the other treatments. Under well-watered conditions, no significant differences among treatments were observed, with generally higher values than those recorded under water-deficit (Fig. 7B).

For CAT activity, under water-deficit conditions, control plants showed the highest activity (6188.27), followed by Si (3237.65), whereas CaO (766.46) and Si + CaO (733.02) showed lower values (Fig. 7C). Under well-watered conditions, no significant differences among treatments were observed.

For APX activity, under water-deficit conditions, CaO treatment exhibited the highest activity (90277.78), followed by the control treatment (61620.37), whereas Si (35692.24) and Si + CaO (27857.14) presented lower values (Fig. 7D). Under well-watered conditions, no significant differences among treatments were detected.

5.4. Discussion

Water-deficit stress impaired ecophysiological performance, biochemical responses, and plant growth, as reflected by reductions in chlorophyll indices, alterations in chlorophyll *a* fluorescence kinetics, and increased stress-related markers such as proline accumulation and antioxidant enzyme activity. These responses indicate disturbances in the photosynthetic apparatus and cellular redox balance, which are typical consequences of limited water availability [1,2].

The application of particle films based on silicon (Si) and calcium oxide (CaO), particularly when applied in combination, modulated these responses by promoting greater functional stability of the photosynthetic apparatus. The increased chlorophyll content and chlorophyll *a/b* ratio observed under Si + CaO treatment suggest improved preservation of antenna complexes and greater efficiency in light energy absorption, supporting the maintenance of photosynthetic activity under stress conditions. These findings are consistent with the role of silicon in maintaining structural and functional integrity of leaves, as well as with the effects of calcium-based particle films in modulating leaf–radiation interactions [21,22,23].

Chlorophyll *a* fluorescence responses further support this mechanism. Reductions in the K and J steps of the OJIP curve indicate lower impairment of the oxygen-evolving complex and greater electron transport efficiency between QA and QB in photosystem II [11, 13]. Furthermore, the enhancement of the I–P phase suggests increased reduction capacity of the plastoquinone pool and improved photosystem I performance, indicating stronger functional coordination between photosystems [24,25]. These responses were corroborated by increased ET0/TR0 and ET0/ABS values and reduced M0, indicating greater efficiency in light energy utilization and reduced initial photochemical damage to PSII [12].

At the biochemical level, antioxidant metabolism revealed a functional reorganization in response to the treatments. Variations in enzyme activity across irrigation regimes and treatments indicate the coexistence of distinct oxidative stress regulation strategies. The higher SOD activity observed under well-watered conditions may be associated with increased metabolic activity and basal superoxide generation due to higher photosynthetic electron flow.

In contrast, CAT and APX primarily respond to H_2O_2 accumulation under stress conditions, reflecting downstream detoxification steps within the antioxidant cascade [26,27].

The increased CAT activity observed in control plants under water-deficit conditions suggests greater H_2O_2 accumulation and, consequently, a higher demand for detoxification, characterizing a reactive antioxidant response. Conversely, the lower antioxidant enzyme activities observed in plants treated with Si and CaO, particularly under combined application, indicate a shift in antioxidant regulation. Under these treatments, reduced enzyme activity does not appear to reflect impaired defense capacity, but rather lower oxidative pressure resulting from reduced ROS generation.

This interpretation is supported by chlorophyll fluorescence responses, which demonstrated improved electron transport efficiency and lower energy dissipation under Si + CaO treatment. Enhanced photochemical performance likely reduced over-reduction of the electron transport chain and consequently lowered the probability of ROS formation within the photosynthetic apparatus [12, 25]. This pattern is consistent with a preventive stress-response mechanism, contrasting with the reactive activation of antioxidant defenses and suggesting greater physiological stability under water-deficit conditions [28,4].

The APX response under water-deficit conditions further supports this interpretation. Higher APX activity in CaO-treated plants suggests greater reliance on the ascorbate–glutathione cycle for H_2O_2 detoxification. In contrast, lower APX activity observed under Si and Si + CaO treatments reinforces the hypothesis of reduced oxidative pressure, indicating that modulation of antioxidant metabolism occurs not only through enzymatic activation but also through restriction of ROS generation.

This pattern was also consistent with proline accumulation. Greater proline content in control plants under water-deficit conditions indicates higher stress intensity, whereas reduced accumulation in Si- and CaO-treated plants suggests a lower requirement for osmotic adjustment and reduced physiological disturbance[29,21].

From a mechanistic perspective, the observed responses may be attributed to complementary functions of Si and CaO. Silicon contributes to maintenance of plant water status, structural protection, and modulation of antioxidant metabolism, whereas calcium is involved in membrane stabilization and cellular signaling associated with stress responses [4, 5, 29]. The combined application of these compounds appears to potentiate these effects, promoting greater functional stability of the photosynthetic apparatus and improved redox regulation.

Morpho agronomic responses indicated that treatment effects were not uniform across different levels of plant organization. Increased leaf area under CaO treatment during water-deficit conditions suggests a potential role of calcium in supporting leaf expansion under stress [30]. In contrast, the combined Si + CaO treatment did not promote similar increases in leaf area, despite its positive effects on photochemical performance and redox regulation. This apparent dissociation between growth-related and photochemical responses indicates that improvements in photosynthetic functionality were not necessarily accompanied by greater vegetative expansion. Such responses suggest that different physiological processes may exhibit distinct sensitivities to Si and CaO under water-deficit conditions, highlighting the complexity of plant acclimation to drought stress [31,32].

Overall, the results demonstrate that the combined application of Si and CaO promotes physiological reprogramming characterized by maintenance of photochemical efficiency, stabilization of the photosynthetic apparatus, and modulation of antioxidant metabolism. This coordinated response limits ROS generation, reduces the requirement for activation of defense mechanisms, and contributes to greater physiological stability under water-deficit conditions.

5.5. Conclusions

The combined application of Si and CaO alleviated the effects of water-deficit stress and promoted marked changes in plant physiological responses. By maintaining photochemical

efficiency and improving electron transport performance, this treatment was associated with lower activation of antioxidant defenses and reduced accumulation of Osmo protective compounds. Together, these responses support the hypothesis of a shift from a predominantly reactive stress-response pattern toward a more preventive strategy based on improved photochemical regulation and redox homeostasis. The results indicate that the integrated modulation of photosynthetic performance and antioxidant metabolism plays a central role in water-deficit tolerance and may be enhanced by the combined application of Si and CaO.

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6. ARTIGO 3
CHLOROPHYLL FLUORESCENCE AND MANAGEMENT VARIABLES IMPROVE THE PREDICTIVE UNDERSTANDING OF 'MINI JACK' PUMPKIN YIELD

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ABSTRACT
Crop productivity results from the interaction among physiological processes, plant growth, and crop management practices, making its prediction challenging for machine learning models with different learning structures. This study evaluated the performance of Linear Regression (LR), Random Forest (RF), and SMOreg This study used 10-fold cross-validation to evaluate the performance of Linear Regression (LR), Random Forest (RF), and SMOreg in predicting the productivity of 'Mini Jack' pumpkin (Cucurbita moschata). Three sets of predictor variables were assessed: Pigments, consisting of chlorophyll indices; OJIP, comprising parameters derived from chlorophyll *a* transient fluorescence; and Physiological, integrating OJIP parameters, chlorophyll indices, and biometric traits. In addition, a complementary analysis was performed by incorporating crop management variables, namely irrigation regime and CaO concentration. The pigment dataset alone exhibited the lowest predictive performance, indicating that chlorophyll indices were insufficient to capture the complexity underlying crop productivity. The inclusion of OJIP parameters improved model performance, with Random Forest showing the highest predictive accuracy, highlighting its ability to capture complex relationships among interdependent photochemical attributes. The integration of photochemical, pigment-related, and biometric information provided the best predictive performance, with SMOreg outperforming the other algorithms. The inclusion of crop management variables maintained high predictive accuracy and further emphasized the importance of cultivation conditions for representing crop productivity. These findings demonstrate that algorithm performance depends on the informational structure of the predictor variables and that integrating physiologically and agronomically complementary variables enhances the ability to predict crop productivity.

Keywords: Chlorophyll fluorescence, OJIP transient, Ecophysiological traits, Predictive modeling, Crop management.

6.1. Introduction

Crop productivity results from the interaction among physiological processes, environmental conditions, and crop management practices, making its prediction a complex task. Changes in water and nutrient availability alter photosynthetic performance, plant growth, and assimilate partitioning, ultimately affecting yield formation (Ansarifar et al., 2021; Jabed and Murad, 2024).

In this context, models capable of linking physiological and agronomic responses to crop performance can improve the understanding of plant responses to cultivation conditions and assist in identifying indicators associated with yield maintenance under contrasting environmental conditions (Jabed and Murad, 2024).

Among the tools available for assessing plant physiological status, chlorophyll *a* fluorescence provides a rapid and non-destructive approach for evaluating the functioning of the photosynthetic apparatus (Kalaji et al., 2016). The OJIP transient offers detailed information on energy absorption and trapping, excess energy dissipation, reaction center activity, and electron transport along the photosynthetic electron transport chain (Strasser et al., 2004; Kalaji et al., 2016).

Although these processes are closely associated with carbon assimilation and yield formation, crop productivity reflects the integration of multiple physiological responses rather

than individual processes alone (Song and Zhu, 2024). Therefore, combining photochemical parameters with pigment, biometric, and crop management information may enhance the ability to model crop productivity (Pathak et al., 2023).

Despite recent advances in agricultural prediction, most predictive models rely primarily on meteorological, soil, spectral, genetic, or remote sensing data, whereas the predictive potential of variables directly related to plant physiological functioning remains comparatively underexplored (Pathak et al., 2023; Kick et al., 2023; Jabed and Murad, 2024). Chlorophyll fluorescence parameters have been widely used to detect plant stress and characterize changes in the photosynthetic apparatus (Kalaji et al., 2016); however, their integration with pigment, biometric, and crop management variables for crop productivity prediction still requires further investigation.

Within this framework, machine learning provides powerful tools for integrating multiple sources of information and identifying patterns associated with crop productivity (Kick et al., 2023 Jabed and Murad, 2024). Comparing algorithms with distinct learning mechanisms makes it possible to determine whether the relationships between predictor variables and crop productivity can be adequately represented by linear models or whether approaches capable of capturing nonlinear interactions provide greater predictive accuracy (Shahhosseini et al., 2021; Jabed and Murad, 2024). Likewise, organizing predictors into progressively more comprehensive datasets enables the contribution of different sources of information to productivity prediction to be assessed, as well as the predictive gains achieved through the incorporation of complementary variables (Kick et al., 2023; Pathak et al., 2023). This approach may contribute to identifying yield-related indicators and support the development of data-driven crop monitoring strategies (Jabed and Murad, 2024).

Therefore, this study evaluated the performance of Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SVR), implemented through the SMOreg algorithm, for predicting the estimated fruit yield of 'Mini Jack' pumpkin (*Cucurbita moschata* Duchesne) grown under different irrigation regimes and CaO particle film concentrations. Models based on chlorophyll pigments, OJIP fluorescence parameters, and integrated physiological variables were compared, and the effect of incorporating crop management information on predictive performance was also evaluated.

6.2. Materials and methods

6.2.1. Data source and dataset organization

The dataset used for predictive modeling was obtained from a field experiment conducted with 'Mini Jack' pumpkin (*Cucurbita moschata* Duchesne) grown under different water availability regimes and calcium oxide (CaO) concentrations applied as a foliar particle film.

The experiment was conducted at the Experimental Farm of the Federal University of Sergipe, Brazil. The region has a mean annual temperature of 25.2 °C and an average annual precipitation of approximately 1,300 mm, concentrated between April and September. The experimental design was a randomized complete block design arranged in a 2 × 4 factorial scheme, consisting of two irrigation regimes corresponding to 100 and 66% of water replacement and four CaO concentrations (0, 2.5, 5.0, and 7.5%). The combination of these factors resulted in eight treatments with eight replicates, totaling 64 plants, each considered an independent observation for predictive modeling.

The dataset comprised variables related to the photochemical activity of the photosynthetic apparatus, photosynthetic pigment indices, fruit biometric characteristics, crop management conditions, and the estimated fruit yield per plant.

6.2.2. Determination of fruit yield per plant

At the end of the experiment, the fruits were harvested and individually identified according to their plant of origin. Each treatment consisted of eight plants, yielding approximately 80 fruits per treatment, with an average production of ten fruits per plant.

The fruits from each plant were weighed, and the mean individual fruit weight was determined separately for each of the 64 plants. The estimated fruit yield per plant was then calculated as:

$$PEPi = MMFi \times NF$$

where *PEPi* represents the estimated yield of plant *i*, expressed as g plant^{-1}; *MMFi* is the mean individual fruit weight of fruits harvested from plant *i*, expressed in g fruit^{-1}; e *NF* is the average number of fruits per plant, fixed at 10 fruits plant^{-1}.

6.2.3. Construction of predictor datasets

To investigate the influence of the nature and degree of integration of input information on the prediction of estimated fruit yield, three predictor datasets were constructed.

The Pigments dataset consisted exclusively of chlorophyll *a* (Chl *a*), chlorophyll *b* (Chl *b*), total chlorophyll (Chl total), and the Chl *a*/Chl *b* ratio. This dataset was used to evaluate the predictive ability of photosynthetic pigment information alone.

The OJIP dataset comprised 17 photochemical parameters derived from chlorophyll *a* fluorescence: M0 (normalized initial slope of the fluorescence transient), ET0/TR0 (probability that a trapped electron moves further along the electron transport chain beyond Quinone a), OEC (oxygen-evolving complex), ET0/ABS (quantum yield of electron transport), ABS/RC (photon absorption flux per active reaction center), TR0/RC (maximum trapped exciton flux per active PSII reaction center), ET0/RC (electron transport flux per active PSII reaction center), RE0/RC (electron flux reducing PSI end electron acceptors per reaction center), DI0/RC (energy dissipation flux per reaction center), ABS/CS0 (photon absorption per excited cross-section), TR0/CS0 (maximum trapped exciton flux per cross-section), DI0/CS0(energy dissipation per cross-section), RC/CS (active reaction centers per cross-section), RC/ABS (active reaction centers per absorbed light), PIABS(performance index on an absorption basis), PIABST (total performance index) e DFABS (driving force on an absorption basis). This dataset was used to investigate the predictive potential of photochemical information alone.

The Physiological dataset integrated the 17 OJIP parameters, the four chlorophyll indices, and the biometric traits of fruit width and fruit length. This dataset was used to evaluate the predictive performance obtained by integrating photochemical, pigment-related, and biometric information. Three regression algorithms were evaluated: Linear Regression (LR), Random Forest for regression (RF), and Support Vector Regression (SVR), implemented through the SMOreg algorithm.

In addition, a complementary analysis was performed to investigate the contribution of crop management variables to yield prediction. In this analysis, irrigation regime and CaO concentration were incorporated as numerical variables into the physiological and biometric dataset, allowing their relative contribution to be evaluated together with attributes related to photochemical functioning, pigment content, and fruit biometric characteristics.

6.2.4. Development of machine learning models

The predictive models were developed using WEKA software (version 3.8) and three regression algorithms with distinct learning mechanisms: Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SVR), implemented through the SMOreg algorithm. Each algorithm was applied independently to the three predictor datasets, allowing the effects of both the nature of the input information and the differences in algorithm performance on estimated fruit yield prediction to be evaluated.

6.2.5. Regression algorithms

Linear Regression (LR) was used as a baseline approach to model linear and additive relationships between the predictor variables and the estimated fruit yield. The general model was expressed as:

$$\hat{y} = \beta 0 + \sum_{j=1}^{p} \beta j x j$$

Where $\hat{y}$ represents the predicted estimated yield, $\beta 0$ is the intercept, βj is the regression coefficient associated with predictor variable xj, and p is the number of predictor variables retained in the model. In WEKA, the algorithm was implemented using the configuration LinearRegression -S 0 -R 1.0E-8, with the ridge regularization parameter set to a 1×10^{-8}. The regression equations and coefficients reported in the WEKA output corresponded to models fitted to the complete dataset and were used to characterize the final regression structure. However, the evaluation of predictive performance was based exclusively on the predictions generated by the 10-fold cross-validation procedure.

Random Forest (RF) was used to model nonlinear relationships and complex interactions among the predictor variables. The algorithm combines multiple regression trees constructed from bootstrap samples of the dataset while randomly selecting subsets of predictor variables during tree construction. The ensemble prediction can be expressed as:

$$\hat{y}RF(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

where B represents the number of trees, and $T_b(x)$ is the prediction of the b three for the predictor vector x.

In WEKA, the Random Forest algorithm was implemented using the configuration RandomForest -P 100 -I 100 -K 0 -M 1.0 -V 0.001 -S 1, corresponding to 100 trees, a bagging sample size equivalent to 100% of the training instances, automatic determination of the number of predictor variables considered at each split, a minimum of one instance per leaf, a numerical tolerance of 0.001, and a random seed of 1.

Support Vector Regression (SVR) was implemented using the SMOreg algorithm. This method estimates a function that relates the predictor variables to a continuous response while balancing model complexity and prediction error. The general function can be expressed as:

$$f(x) = w^T \phi(x) + b$$

where w represents the weight vector, b is the intercept, and $\phi(x)$ denotes the transformation of the predictor variables into the feature space defined by the kernel function. SMOreg was implemented with a complexity parameter of (C = 1.0), filter setting -N 0, the RegSMOImproved optimizer, and a PolyKernel with exponent (E = 1.0). The complete configuration used was SMOreg -C 1.0 -N 0 with RegSMOImproved -T 0.001 -V -P 1.0E-12 -L 0.001 -W 1 and PolyKernel -E 1.0. The weights reported in the WEKA output correspond to the model fitted to the complete dataset and were used solely to interpret the model structure. These weights were not considered equivalent to the permutation-based importance measures used in the Random Forest analysis.

6.2.6. Model validation

The predictive performance of the nine combinations of predictor datasets and regression algorithms was evaluated using 10-fold cross-validation. In this procedure, the 64 observations were randomly partitioned into ten subsets. At each iteration, nine subsets were

used for model training, while the remaining subset was used for validation. This process was repeated until every observation had been used once as part of the validation set.

For each combination of predictor dataset and algorithm, the individual predictions generated during cross-validation were exported from WEKA. The output files contained the instance identifier and the corresponding columns for the observed value, predicted value, and individual prediction error: inst#, actual, predicted, and error.

The observed versus predicted yield plots and the performance metrics subsequently calculated in R were based exclusively on the predictions obtained from the cross-validation procedure rather than on predictions generated by models fitted and evaluated using the complete dataset, thereby avoiding overfitting.

6.2.7. Model performance evaluation metrics

Model performance was evaluated using the Pearson correlation coefficient between observed and predicted values (r), the coefficient of determination (R^2), the mean absolute error (MAE), and the root mean square error (RMSE). The R^2 value used in the observed versus predicted plots was calculated as:

$$R^2 = r^2$$

The mean absolute error (MAE) was calculated as:

$$MAE = \frac{1}{n}\sum_{y=1}^{n} |yi - \hat{y}\, i|$$

and the root mean square error (RMSE) was calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{y=1}^{n} (yi - \hat{y}i)^2}$$

Where yi is the observed yield of plant i, $\hat{y}i$ is the yield predicted by the algorithm, and (n) is the total number of observations. Higher predictive performance was associated with higher values of r and R^2 and lower values of MAE and RMSE.

6.2.8. Processing of predictions, visualization, and graph generation in R

The individual predictions obtained from the cross-validation procedure were subsequently processed in the R statistical environment. A custom computational script was used to identify, within the WEKA output files, the table beginning with the header inst#, actual, predicted, error, import the observed and predicted values, and organize the results according to the evaluated algorithm. Based on the 64 individual predictions generated for each model, the Pearson correlation coefficient (r), coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) were recalculated. The resulting values were compared with the corresponding metrics reported by WEKA, showing complete agreement, with only minor differences attributable to decimal rounding.

Scatter plots of observed versus predicted fruit yield were generated using the ggplot2 package in R. The graphs included the individual observations, a 1:1 reference line, and a fitted linear regression line between the observed and predicted values.

6.2.9. Variable importance analysis

As a complementary analysis to the predictive evaluation performed in WEKA, variable importance in the Random Forest model was assessed separately in the R environment. The

dataset was imported in ARFF format, and a complementary Random Forest model was fitted using the randomForest package with 100 trees (*ntree* = 100) and variable importance enabled (*importance* = TRUE). Predictor importance was quantified using permutation-based importance, expressed as the percentage increase in mean squared error (%IncMSE). This approach evaluates the change in model performance after randomly permuting the values of each predictor variable. Higher %IncMSE values were interpreted as indicating a greater contribution of the corresponding variable to the predictive performance of the model.

The predictor variables were ranked in descending order according to %IncMSE, and the ten variables with the highest values were selected for graphical representation. The variable importance analysis was considered complementary and independent of the model performance evaluation conducted in WEKA. Accordingly, the cross-validation metrics reported for the Random Forest model were obtained from the models developed in WEKA, whereas the Random Forest model fitted in R was used exclusively to assess the relative importance of the predictor variables.

6.3. Results

6.3.1 Predictive performance of machine learning algorithms

The predictive performance of the machine learning algorithms varied according to the predictor dataset used for yield prediction. In the model based exclusively on photosynthetic pigment indices, all algorithms exhibited low predictive performance, as indicated by the correlation coefficients obtained. SMOreg achieved the highest correlation coefficient (r = 0.40), followed by Linear Regression (LR) (r = 0.35) and Random Forest (RF) (r = 0.34) (Figure 1).

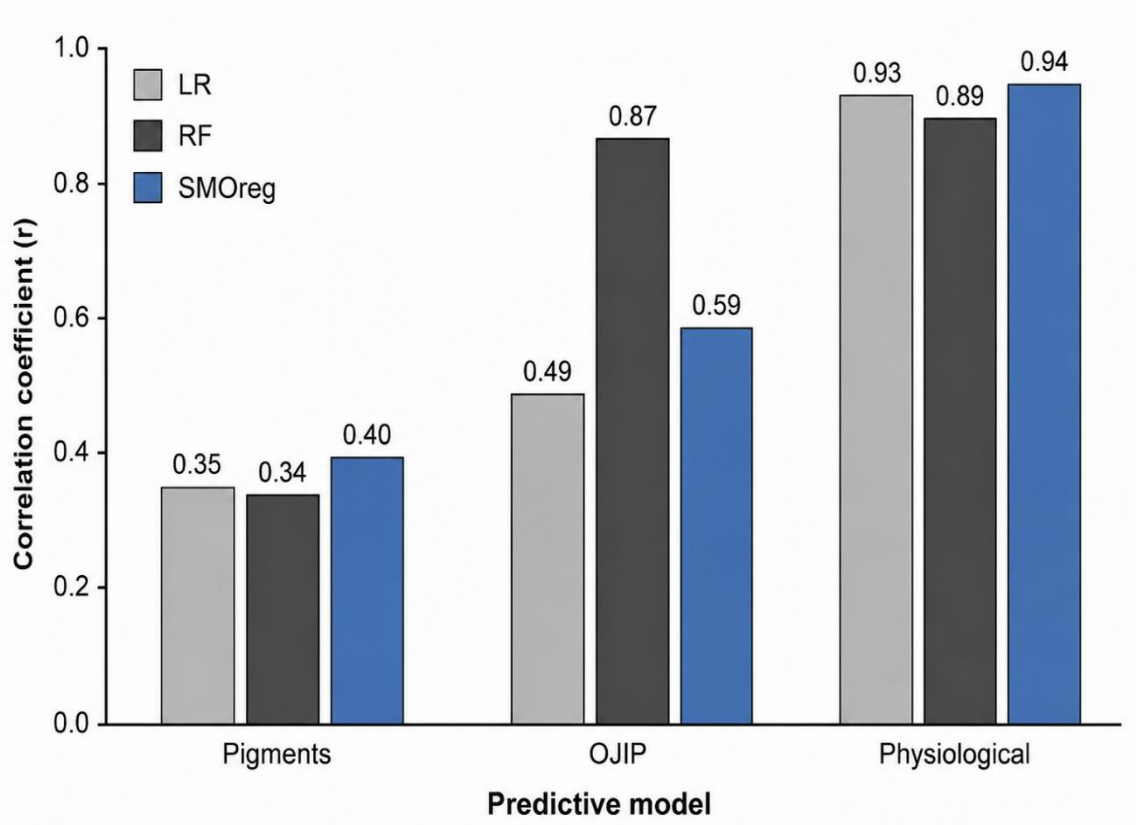

Figure 1. Predictive performance of Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SMOreg) models using different sets of predictor variables. The models were developed based on pigment traits, chlorophyll fluorescence (OJIP) parameters, and the integrated physiological dataset. Model performance is expressed by the Pearson correlation

coefficient (r) between observed and predicted productivity obtained by 10-fold cross-validation. Higher correlation coefficients indicate greater predictive accuracy.

The use of chlorophyll *a* fluorescence (OJIP) parameters for yield prediction substantially improved model performance. Within this predictor dataset, RF achieved the highest predictive performance ($r = 0.87$), whereas SMOreg ($r = 0.59$) and LR ($r = 0.49$) showed lower predictive accuracy.

The best predictive performance was obtained with the Physiological dataset, which integrated OJIP fluorescence parameters, photosynthetic pigment indices, and fruit biometric traits. Under this dataset, all algorithms exhibited high correlation coefficients. SMOreg achieved the highest performance ($r = 0.94$), followed by LR ($r = 0.93$) and RF ($r = 0.89$). Overall, the predictive performance of the algorithms increased progressively as more comprehensive predictor datasets were used, with the Physiological dataset consistently providing the highest predictive accuracy regardless of the algorithm employed

6.3.2 Variable importance for yield prediction

Within the OJIP dataset, the importance of predictor variables differed among the evaluated algorithms. In the Random Forest (RF) model, the greatest contributions to yield prediction were observed for DI0/RC (%IncMSE = 6,28), TR0/CS0 (6,14), ABS/CS0 (5,84), M0 (5,34), ET0/RC (5,34) e RE0/RC (4,61), seguidas por ET0/TR0 (4,59), ABS/RC (4,17) and OEC (3,84) (Figure 2).

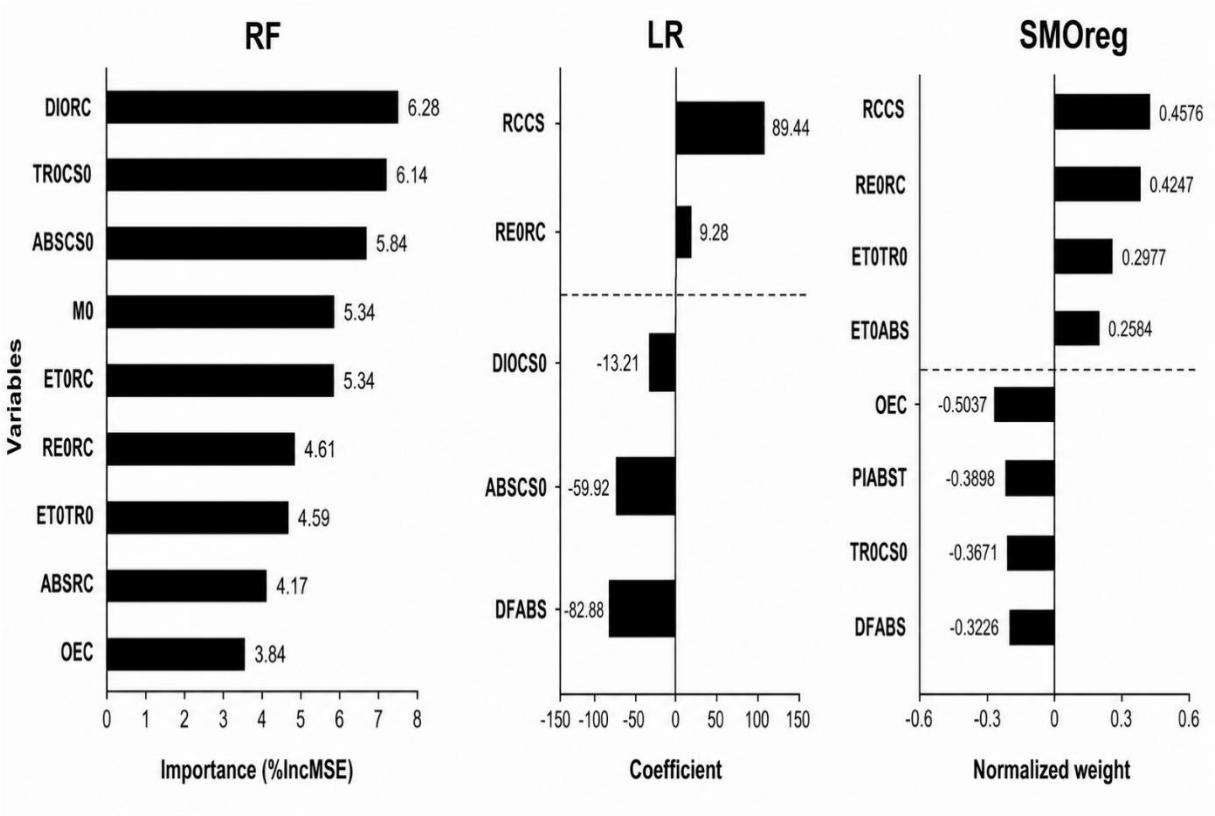

Figure 2. Relative contribution of chlorophyll fluorescence (OJIP) parameters to productivity prediction using three machine learning algorithms. The left panel shows the variable importance estimated by Random Forest (RF), expressed as the percentage increase in mean squared error (%IncMSE). The central panel presents the regression coefficients retained in the final Linear Regression (LR) model. The right panel shows the normalized weights obtained from the Support Vector Regression (SMOreg) model. Positive coefficients or weights indicate variables positively associated with predicted productivity, whereas negative values indicate variables with a negative contribution to model predictions.

For Linear Regression (LR), the M5 method retained five of the 17 predictor variables initially included in the model. RC/CS and RE0/RC exhibited positive unstandardized regression coefficients (89.44 and 9.28, respectively), whereas DI0/CS0 (−13,21), ABS/CS0 (−59,92) and DFABS (−82,88) showed negative coefficients, indicating an inverse association with estimated fruit yield.

In the SMOreg model, fitted with internal attribute normalization and a first-degree PolyKernel, RC/CS showed the highest positive weight in the normalized feature space (0.4576), followed by RE0/RC (0,4247), ET0/TR0 (0,2977) and ET0/ABS (0,2584). In contrast, OEC exhibited the largest negative weight (−0.5037), followed by PIABS total (−0,3898), TR0/CS0 (−0,3671) and DFABS (−0,3226).

Although the algorithms prioritized different sets of predictor variables, convergence was observed for several attributes. RE0/RC was selected by all three algorithms, whereas RC/CS was identified by both Linear Regression (LR) and SMOreg, exhibiting the greatest positive contribution in these models. Similarly, OEC, TR0/CS0, ABS/CS0 and DFABS ranked among the most influential variables in two of the three algorithms evaluated. In contrast, DI0/RC, M0 e ET0/RC were identified as important predictors exclusively by Random Forest (RF), highlighting differences in predictor selection among the machine learning methods.

The importance of predictor variables in the Physiological dataset differed among the evaluated algorithms. In the Random Forest (RF) model, fruit biometric traits showed the greatest contributions to yield prediction, with fruit length (%IncMSE = 10.21) and fruit width (6.15) ranking as the most important predictors. Among the physiological variables, DI0/RC (5,26), RC/ABS (3,98), M0 (3,61), TR0/RC (3,32), DFABS (2,97), ET0/RC (2,74), DI0/CS0 (2,55) and total chlorophyll (2,31) were also among the most influential predictors. (Figure 3).

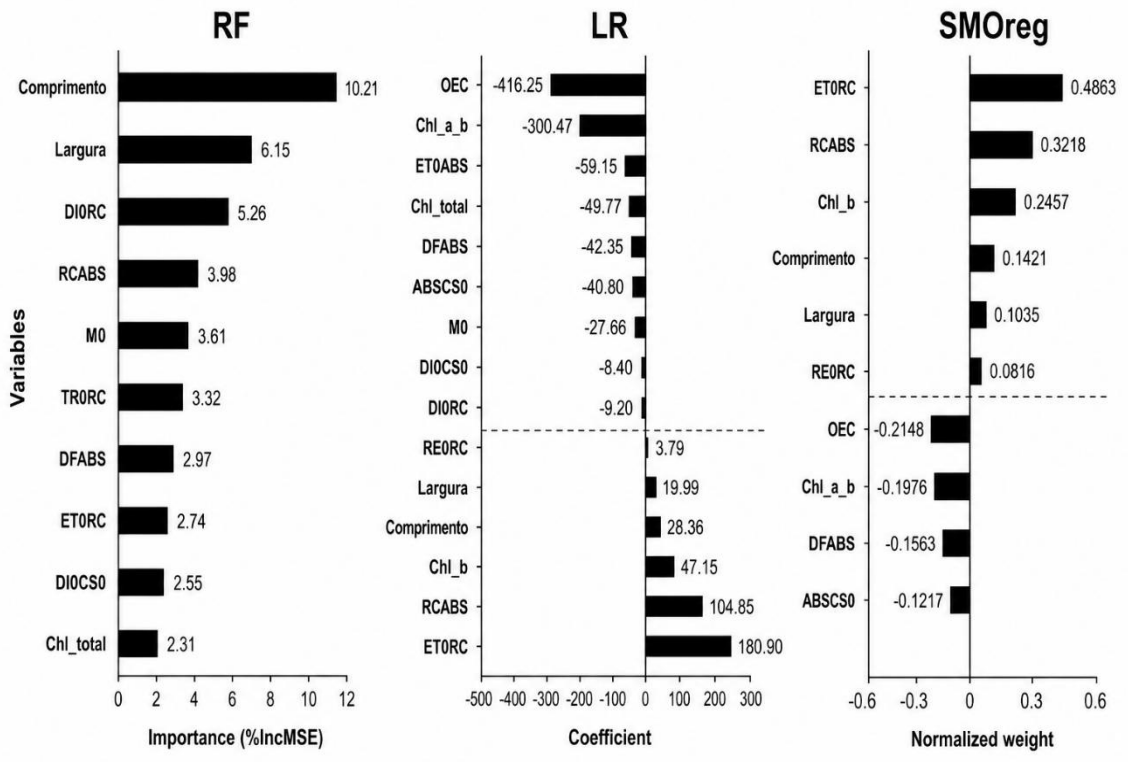

Figure 3. Relative contribution of physiological variables to productivity prediction using three machine learning algorithms. The left panel shows the variable importance estimated by Random Forest (RF), expressed as the percentage increase in mean squared error (%IncMSE). The central panel presents the regression coefficients retained in the final Linear Regression

(LR) model. The right panel shows the normalized weights obtained from the Support Vector Regression (SMOreg) model. The physiological dataset comprised chlorophyll fluorescence (OJIP) parameters, chlorophyll pigments, and biometric traits. Positive coeffi cients or weights indicate variables positively associated with predicted productivity, whereas negative values indicate variables with a negative contribution to model predictions.

In the Linear Regression (LR) model, ET0/RC exhibited the highest positive regression coefficient (180.90), followed by RC/ABS (104.85), chlorophyll b (47.15), fruit length (28.36), fruit width (19.99), and RE0/RC (3,79). In contrast, OEC showed the largest negative coefficient (−416.25), followed by the chlorophyll a/b ratio (−300.47), ET0/ABS (-59,15), total chlorophyll (-49,77), DFABS (-42,35), ABS/CS0 (-40,80), M0 (-27,66), DI0/RC (-9,20) and DI0/CS0 (-8,40).

In the SMOreg model, ET0/RC had the highest positive normalized weight (0.4863), followed by RC/ABS (0.3218), chlorophyll b (0.2457), fruit length (0.1421), fruit width (0.1035), and RE0/RC (0,0816). The largest negative weights were observed for OEC (−0.2148), the chlorophyll a/b ratio (−0.1976), DFABS (-0,1563) and ABSCS0 (-0,1217).
Despite differences in variable selection among the algorithms, a high degree of agreement was observed for several predictors. ET0/RC, RC/ABS, RE/0RC, fruit length, fruit width, OEC, DFABS and ABS/CS0 were selected by two or more algorithms. Notably, fruit length emerged as the most important predictor in the Random Forest model and remained among the most influential variables in both LR and SMOreg. Likewise, ET0/RC consistently showed high relevance across all three algorithms, exhibiting the largest positive regression coefficient in LR and the highest normalized weight in SMOreg

6.3.3 Yield prediction

The relationship between observed and predicted yield confirmed the differences in algorithm performance for the model based exclusively on OJIP parameters (Figure 4).

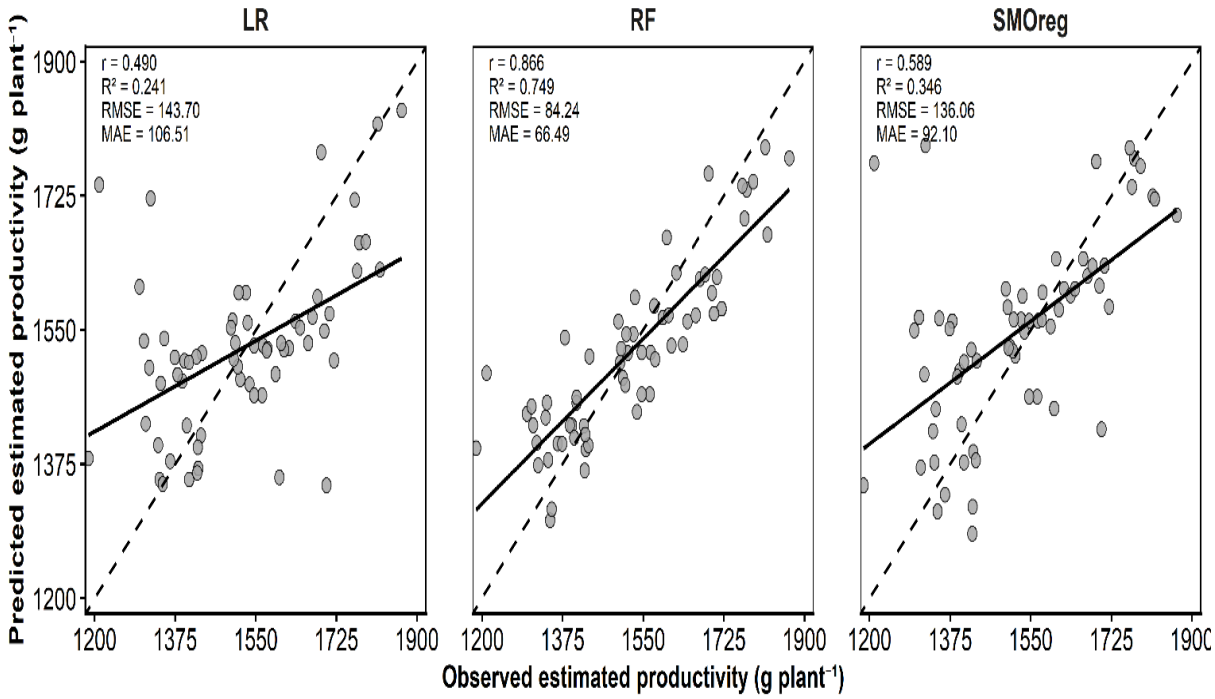

Figure 4. Relationship between observed and predicted estimated productivity using the OJIP model. Predictions were obtained by 10-fold cross-validation using Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SMOreg). The dashed line represents the 1:1 relationship, whereas the solid line represents the fitted regression.

Linear Regression (LR) exhibited a wide dispersion of data points relative to the 1:1 identity line, indicating lower agreement between observed and predicted values. Accordingly, this algorithm produced the lowest coefficient of determination (R^2 = 0.241), together with the highest RMSE (143.70 g plant^{-1}) and MAE (106.51 g plant^{-1}) values. Random Forest (RF) showed closer agreement between observed and predicted values, with data points more tightly distributed along the 1:1 identity line and lower residual dispersion. This performance resulted in the highest coefficient of determination (R^2 = 0.749) and the lowest RMSE (84.24 g plant^{-1}) and MAE (66.49 g plant^{-1}) values, demonstrating superior predictive accuracy compared with the other algorithms.

The intermediate performance of SMOreg suggests that, although the algorithm is capable of modeling nonlinear relationships, OJIP parameters alone do not provide sufficient information to explain the full variability in yield. In contrast, Random Forest showed a greater ability to capture the complex interactions among chlorophyll fluorescence variables, resulting in closer agreement between observed and predicted values, particularly within the higher yield range.

Overall, Random Forest exhibited the highest agreement between observed and predicted values, whereas LR and SMOreg showed greater point dispersion, indicating lower accuracy in yield estimation when OJIP parameters were used as the sole predictor variables

The use of the Physiological dataset resulted in high agreement between observed and predicted yield values for all three algorithms evaluated (Figure 5).

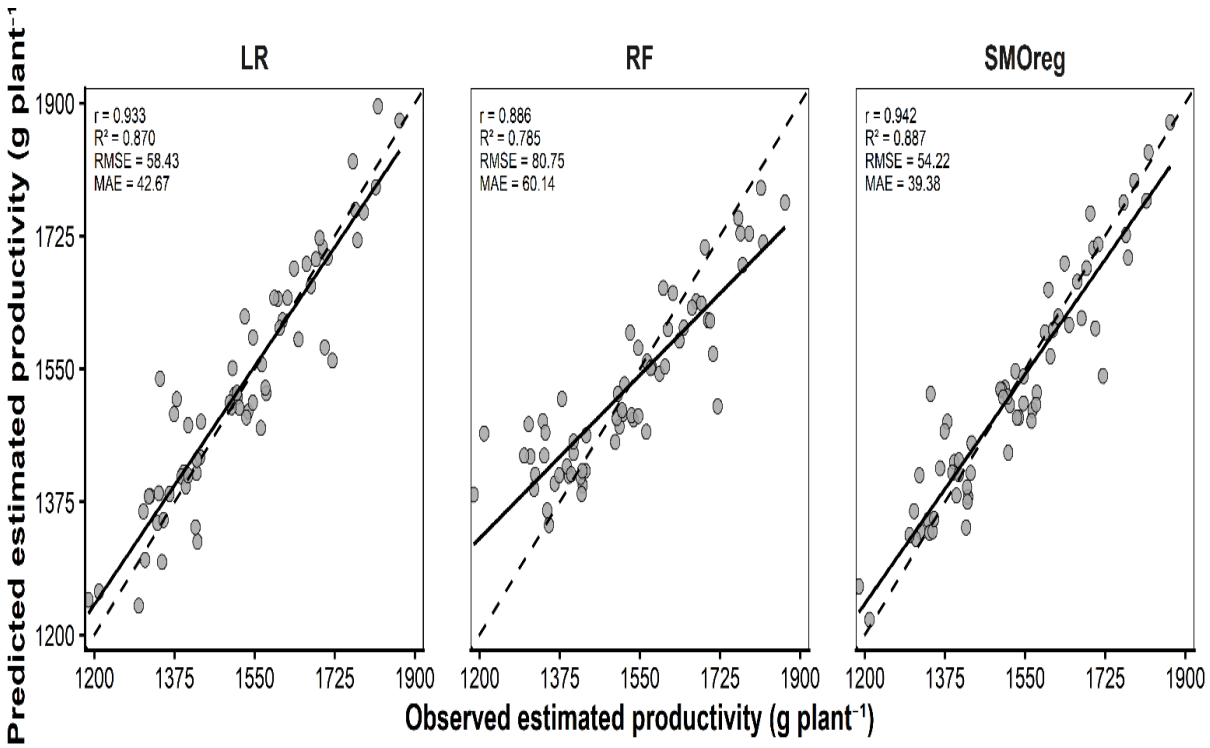

Figure 5. Relationship between observed and predicted estimated productivity obtained using the physiological model. Predictions were generated by Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SMOreg) based on chlorophyll fluorescence (OJIP) parameters, chlorophyll pigments, and biometric traits. Model performance was evaluated by 10-fold cross-validation. The dashed line represents the 1:1 relationship between observed and predicted productivity, whereas the solid line corresponds to the fitted regression line. Performance metrics (Pearson's correlation coefficient, *r*; coefficient of determination, R^2; root mean squared error, RMSE; and mean absolute error, MAE) are presented within each panel.

Linear Regression (LR) showed data points closely distributed around the 1:1 identity line, reflecting high predictive accuracy, with a coefficient of determination (R^2) of 0.870, an RMSE of 58.43 g plant^{-1}, and an MAE of 42.67 g plant^{-1}.

Random Forest (RF) also exhibited high agreement between observed and predicted values (R^2 = 0.785), although a greater dispersion of data points around the identity line was observed compared with the other algorithms. Consequently, RF yielded an RMSE of 80.75 g plant^{-1} and an MAE of 60.14 g plant^{-1}.

SMOreg provided the best fit between observed and predicted values, with data points closely clustered along the 1:1 identity line and the lowest visual dispersion among the evaluated algorithms. This performance resulted in the highest coefficient of determination (R^2 = 0.887), as well as the lowest RMSE (54.22 g plant^{-1}) and MAE (39.38 g plant^{-1}) values.
Overall, all three algorithms exhibited high predictive performance when the Physiological dataset was used, with SMOreg providing the best agreement between observed and predicted values, followed by LR, whereas RF showed greater point dispersion and higher prediction errors

6.3.4 Contribution of crop management variables to yield prediction

The inclusion of crop management variables (irrigation and CaO concentration) altered the set of predictors selected by the machine learning algorithms. When analyzed together with chlorophyll fluorescence parameters, photosynthetic pigment indices, and fruit biometric traits, the crop management variables became part of the most influential predictors associated with yield prediction. In the Random Forest (RF) model, irrigation showed the highest relative importance (%IncMSE = 9.02), followed by fruit length (6.37), CaO concentration (6.24), fruit width (4.43), chlorophyll *b* (4,14), DI0/RC (3,95), TR0/CS0 (3,64), the chlorophyll *a/b* ratio (3,27), ET0/RC (3,18) and M0 (2,91).

In the Linear Regression (LR) model, chlorophyll *b* exhibited the highest positive regression coefficient (55.35), followed by fruit length (27.94), fruit width (20.23), and irrigation (1.69). In contrast, the chlorophyll *a/b* ratio showed the largest negative coefficient (−287.69), followed by TR0/CS0 (-112,76), M0 (-33,55) and DI0/RC (-17,23).

In the SMOreg model, fruit length exhibited the highest positive normalized weight (0.5538), followed by fruit width (0.3448), RC/CS (0.2840), RE₀/RC (0.2224), chlorophyll b (0.1344), and irrigation (0.1281). The largest negative weights were observed for total chlorophyll (−0.2867), the chlorophyll a/b ratio (−0.2335), chlorophyll a (−0.2175), and DFABS (-0,1101).

Although each algorithm prioritized different predictor sets, a high degree of agreement was observed for several variables. Fruit length, fruit width, chlorophyll b, and irrigation were selected by more than one algorithm, ranking among the most important predictors of yield in the integrated model. In addition, photochemical parameters such as DI0/RC, TR0/CS0, ET0/RC, RC/CS, RE0/RC and M0, remained among the most relevant predictors, demonstrating that the integration of crop management, growth, and physiological information expanded the set of variables associated with yield prediction (Figure 6).

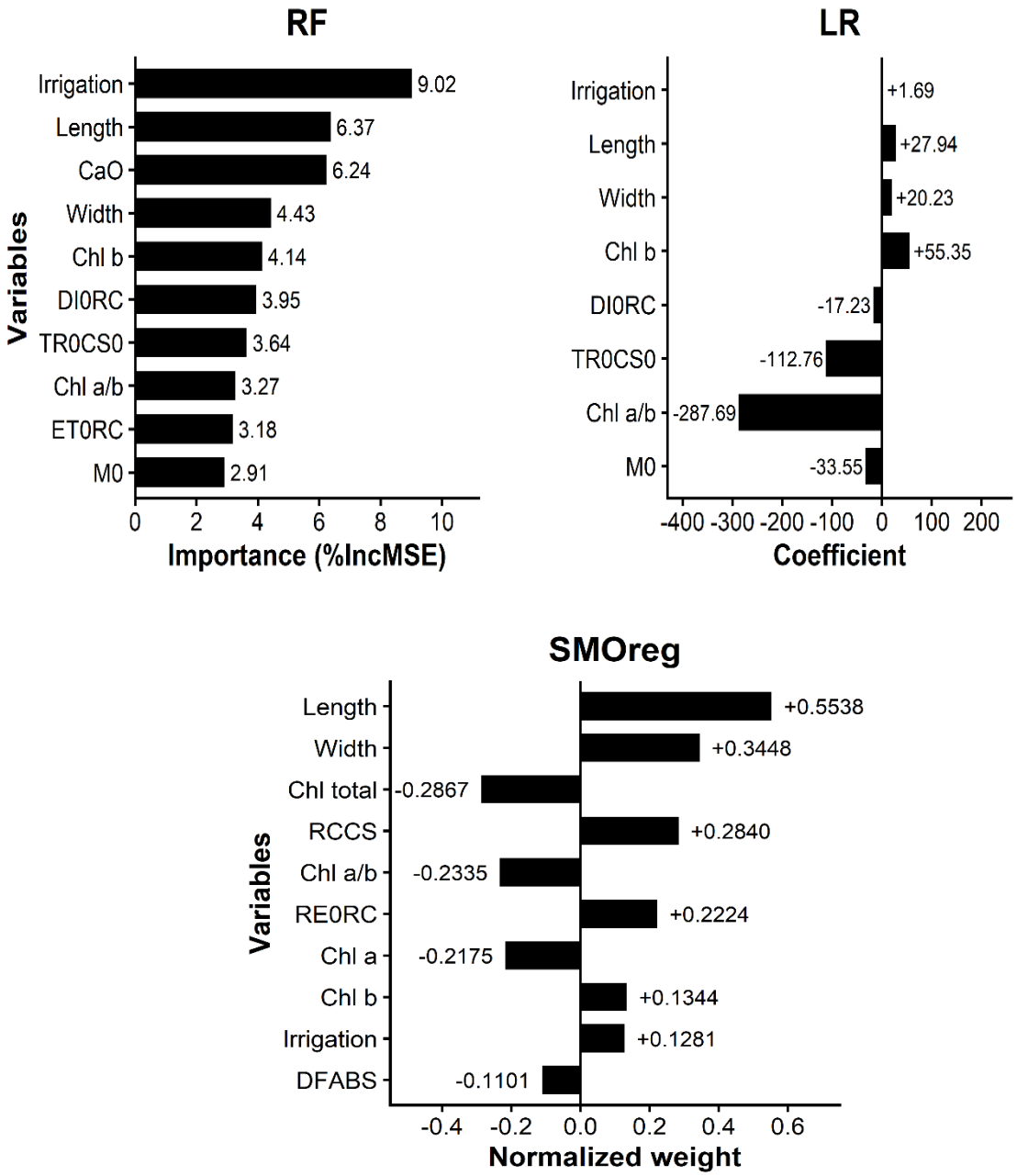

Figure 6. Importance of management variables and associated physiological predictors for productivity prediction in the integrated model. Variable importance estimated by Random Forest (RF), regression coefficients obtained by Linear Regression (LR), and normalized weights estimated by Support Vector Regression (SMOreg). Positive and negative values indicate direct and inverse relationships with predicted productivity, respectively.

6.4. Discussion

Crop productivity results from the interaction among environmental factors, crop management practices, and physiological processes operating across different spatial and temporal scales, making its prediction challenging because of the complex and nonlinear relationships among the variables involved (Ansarifar et al., 2021; Srivastava et al., 2022). In this context, differences in algorithm performance may reflect not only their learning capabilities but also the nature and level of biological information provided by the different predictor datasets.

This relationship was evident in the changes in algorithm performance across the datasets evaluated. When only OJIP parameters were used, Random Forest achieved the highest predictive performance, whereas SMOreg outperformed the other algorithms after the incorporation of photosynthetic pigment indices, fruit biometric traits, and crop management variables. This shift suggests that algorithm performance depends on the correspondence between the learning mechanism of the algorithm and the nature of the relationships embedded in the data (Pathak et al., 2023).

OJIP parameters describe functionally interdependent processes related to excitation energy absorption and trapping, energy dissipation, and electron transport along the photosynthetic electron transport chain (Kalaji et al., 2016). Although these parameters characterize different stages of the photosynthetic process, their relationships with crop productivity are not necessarily direct or proportional, since final yield results from the temporal integration of photochemical, metabolic, and growth processes (Špánić et al., 2021; Ding et al., 2022). Under these conditions, the ability of Random Forest to capture nonlinear relationships and complex interactions may explain its superior performance when the model was trained exclusively with OJIP parameters (Breiman, 2001).

The importance of RE0/RC, RC/CS and DI0/RC reinforces this interpretation. These parameters represent complementary components of the energy dynamics of the photosynthetic apparatus, corresponding, respectively, to the electron flux reducing the end electron acceptors at photosystem I per reaction center, the density of active reaction centers per cross-section, and the energy dissipation flux per active reaction center (Strasser et al., 2004; Tsimilli-Michael, 2020). The recurrent selection of RE0/RC cross all algorithms suggests that maintaining electron transport to the final PSI electron acceptors constitutes an important link between photochemical functioning and crop productivity.

Likewise, the relevance of RC/CS and DI0/RC cross all algorithms suggests that maintaining electron transport to the final PSI electron acceptors constitutes an important link between photochemical functioning and crop productivity. Likewise, the relevance of RE0/RC and RC/ABS among the most relevant predictors indicates that photochemical functioning remained closely associated with crop productivity (Zhang et al., 2024). The combination of these variables enabled the model to relate the efficiency of electron transport to cumulative physiological and growth responses throughout the crop cycle.

This change in the informational structure of the predictor datasets may explain the superior performance of SMOreg after variable integration. Whereas Random Forest performed best when only OJIP parameters were used, SMOreg achieved the highest predictive performance once photochemical, pigment-related, and biometric information was combined. Its superior performance therefore appears to be associated with its ability to represent relationships within predictor datasets integrating multiple levels of biological information and temporal scales (Kick et al., 2023; Shamsuddin et al., 2024). Accordingly, the observed gain in predictive performance resulted not simply from increasing the number of predictors but from incorporating physiologically complementary sources of information.

The inclusion of crop management variables further improved predictive performance, indicating that crop productivity was better represented when cultivation conditions were analyzed together with plant physiological responses (Jabed and Murad, 2024). Water availability ranked among the most influential predictor variables, which is consistent with its central role in regulating stomatal conductance, CO_2 assimilation, electron transport, energy dissipation, and plant growth (Qiao et al., 2024). Thus, irrigation introduced an environmental variable directly associated with the physiological and productive variability observed among plants.

CaO concentration also exhibited high importance in the integrated model, demonstrating that crop management practices contributed valuable information for productivity prediction. The application of particle films can modify the radiative and thermal

environment of the leaf surface, thereby influencing the photochemical and physiological responses of the crop (Silva et al., 2019; Oliveira Júnior et al., 2019).

Accordingly, the combined inclusion of crop management variables, OJIP parameters, photosynthetic pigment indices, and biometric traits enabled the model to represent multiple levels of plant responses, ranging from the environmental conditions that induce or modulate stress to their consequences for photosynthetic functioning, plant growth, and crop productivity.

The persistence of variables related to crop management, photochemical functioning, pigment content, and plant growth among the most relevant predictors demonstrates that crop productivity results from the integration of multiple levels of biological organization. Whereas irrigation and CaO represent management factors that modulate crop development, OJIP parameters characterize photochemical functioning, pigment indices reflect plant physiological status, and biometric traits integrate the cumulative effects of plant development over time (Kalaji et al., 2016; Oliveira Júnior et al., 2019).

This complementarity may explain the superior performance of SMOreg in the integrated model, as combining multiple sources of information provides a more comprehensive representation of the processes underlying crop productivity and enhances the predictive capability of machine learning models (Kick et al., 2023; Shamsuddin et al., 2024). Therefore, the improvement in predictive performance appears to result not only from the choice of algorithm but also from the incorporation of physiologically and agronomically complementary predictor variables.

6.5. Conclusion

The ability to predict the yield of 'Mini Jack' pumpkin depends on both the nature of the predictor variables and the machine learning algorithm employed. Photosynthetic pigment indices alone exhibited limited predictive power, whereas OJIP parameters provided relevant predictive information, particularly when modeled using Random Forest. The integration of photochemical, pigment-related, and biometric information resulted in the highest predictive performance, with SMOreg outperforming the other algorithms. In the complementary analysis, the model demonstrated that the inclusion of crop management variables (irrigation regime and CaO concentration) further improved predictive performance when considered jointly with physiological and biometric responses, highlighting the potential of integrating multiple levels of plant- and management-related information to enhance yield prediction.

6.6. References

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7. CONSIDERAÇÕES FINAIS

Os filmes de partículas à base de CaO possuem potencial efeito mitigador sob condições de déficit hídrico em plantas de abóbora 'Mini Jack', com respostas dependentes da

concentração aplicada. A concentração de 5% favorece a manutenção dos pigmentos fotossintéticos, da eficiência fotoquímica e do transporte de elétrons, refletindo-se em melhor desempenho produtivo, enquanto concentrações mais elevadas podem comprometer essas respostas.

A associação entre Si e CaO amplia a proteção fisiológica das plantas sob déficit hídrico, preservando o aparato fotossintético e modulando as respostas osmóticas e antioxidantes. Além disso, a integração de informações fisiológicas, biométricas e de manejo aumenta a capacidade de predição da produção, evidenciando o potencial do aprendizado de máquina como ferramenta complementar para compreender e predizer o desempenho produtivo da cultura.

Estudos adicionais são necessários para validar essas respostas em diferentes condições ambientais, ciclos de cultivo e escalas de produção, bem como para avaliar a aplicabilidade dos modelos preditivos em conjuntos de dados independentes.