## **Supplementary Information for**

# **Interpretable machine learning-accelerated seed treatment by nanomaterials for environmental stress alleviation**

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This supplementary information file includes:

- Methods S1 to S5
- Figures S1 to S21
- Tables S1 to S6

## **Methods**

**Method S1.** Determination of root:shoot ratio

The root:shoot ratio was calculated as the following equation:

root dry weight  $\times 100\%$ stem dry weight + leaf dry Root:shoot rati weight  $0 = \frac{100t \text{ dy weight}}{1 + 1 + 2t \text{ y}} \times$ 

#### **Method S2.** Determination of SRI

The SRI was calculated as the following equation:

$$
SRI = \sum_{i=1}^{10} \frac{k_i}{k_i^c}
$$

where  $k_i$  is the value of the i<sup>th</sup> endpoint for each treatment, and  $k_i^c$  is the value of the ith endpoint for the control. SRI comprehensively considers the relative value of nano-primed and control treatment in ten biological endpoints, and thus the SRI for control is 10.0.

**Method S3.** Analytical method, instrument parameters, and data acquisition of metabolomics analysis

The samples were separated by Agilent 1290 infinity LC ultra performance liquid chromatography (UHPLC) on a C-18 column (column temperature:40 ℃). The flow rate of gradient elution was set at  $0.4$  ml/min, and the injection volume was  $2 \mu L$ . The mobile phase  $A = 25$  mM ammonium acetate and 0.5% formic acid in water and mobile phase  $B$  = methanol. The gradient elution procedure was as follows: 5% B in the first 0.5 min, linearly increased to 100% in the next 9.5 min, and maintained at 100% for 2 min; then it was linearly decreased to 5% in 6 s and maintained at 5% in the next 3.9 min. The sample was placed in an automatic sampler at 4 ℃ during the whole analysis.

Parameter settings of ESI source: Ion Source Gas1 (Gas1) at 60, Ion Source Gas2 (Gas2) at 60, curtain gas at 30, ion source temperature at 600 ℃, ion spray voltage floating at  $\pm$  5500 V. The instrument was set to collect data in the m/z range of 60-1000 Da in MS only acquisition, and the accumulation time for TOF MS scan was 0.20 s/spectra. The instrument acquired data over the m/z range 25-1000 Da in auto MS/MS acquisition, and the accumulation time for product ion scan was 0.05 s/spectra. Production scans were acquired using information dependent acquisition with high sensitivity mode selected. The parameters were set as follows: the collision energy at 35 V with  $\pm$  15 eV; declustering potential at  $\pm$  60 V (positive and negative modes); exclude isotopes within 4 Da and candidate ions to monitor per cycle at 10.

**Method S4.** Line fitting of SHAP main effects and SHAP interactions

The line fitting was based on python language using "scipy.optimize" and "numpy.polyfit" packages. The fitting equations are described as follows:

(1) Piecewise linear fitting for SHAP main effects of the TEM size of nanoparticles (Fig. 4e):

$$
y = \begin{cases} 2.00 \times 10^{-1} x - 3.87, & x \le 21.50 \text{ nm} \\ 1.50 \times 10^{-3} x + 3.90 \times 10^{-1}, & x > 21.50 \text{ nm} \end{cases}
$$

where x is the TEM size of nanoparticles, and y is the SHAP main effect value.

(2) Linear fitting for SHAP main effects of the zeta potential of nanoparticles (Fig. 4f):

$$
y = -1.14 \times 10^{-2} x - 2.77 \times 10^{-2} x
$$

where x is the zeta potential of nanoparticles, and y is the SHAP main effect value.

(3) Logistic fitting for SHAP interactions between the zeta potential and concentration of nanoparticles (Fig. 4k):

$$
y = \begin{cases} \frac{-2.28}{1 + e^{4.66 + 5.48 \times 10^{-1} x_1}} + 8.39 \times 10^{-1}, & x_2 = 100 \text{ mg/L} \\ \frac{2.29}{1 + e^{10.57 + 9.32 \times 10^{-1} x_1}} - 6.91 \times 10^{-1}, & x_2 = 50 \text{ mg/L} \end{cases}
$$

where  $x_1$  is the zeta potential of nanoparticles,  $x_2$  is the concentration of nanoparticles, and  $y$  is the SHAP interaction value.

(4) Plateau fitting for SHAP interactions between the TEM size and concentration of nanoparticles (Fig. 4l):

$$
y = \frac{-3.96x}{8.51 + x_1} + 3.00, x_2 = 100 \text{ mg/L or } x_2 = 50 \text{ mg/L}
$$

where  $x_1$  is the TEM size of nanoparticles,  $x_2$  is the concentration of

nanoparticles, and  $y$  is SHAP interaction value.

(5) Polynomial fitting for SHAP main effects of the TEM size of nanoparticles (Fig. 5e):

$$
y = 1.66 \times 10^{-6} x^3 - 3.63 \times 10^{-4} x^2 + 2.44 \times 10^{-2} x - 4.27 \times 10^{-1}
$$

where x is the TEM size of nanoparticles, and y is the SHAP main effect value. (6) Polynomial fitting for SHAP main effects of the zeta potential of nanoparticles (Fig. 5f):

$$
y = -5.71 \times 10^{-6} x^3 + 2.49 \times 10^{-4} x^2 + 1.89 \times 10^{-3} x - 8.44 \times 10^{-2}
$$

where x is the zeta potential of nanoparticles, and y is the SHAP main effect value.

**Method S5.** Cost estimate of seed nanopriming (nanoparticles)

Given the following conditions:

ZnO nanoparticle price (30nm, Macklin): RMB ¥ 308 (500 g)

Seed weight: nanoparticle volume: 1:5 g/mL

Planting seeds  $= 22 \text{ kg/ha}$ 

Nanoparticle concentration: 200 mg/L

so, we can estimate the nanoparticle fee.

Nanosuspension volume =  $22 \text{ kg/ha} \times 5 \text{ L/kg} = 110 \text{ L/ha}$ 

Nanoparticle weight = 110 L/ha  $\times$  200 mg/L = 22000 mg/ha = 22 g/ha

Nanoparticle fee = 22 g/ha  $\times$  ¥ 308 ÷ 500 g = ¥ 13.552/ha (around \$ 2/ha)

## **Figures**



**Fig. S1:** TEM images of fourteen low-cost metalloid and metal oxide nanoparticles (SiO<sub>2</sub>, CeO<sub>2</sub>, CuO, Fe<sub>3</sub>O<sub>4</sub>, ZnO,  $\alpha$ -Fe<sub>2</sub>O<sub>3</sub>, and  $\gamma$ -Fe<sub>2</sub>O<sub>3</sub> of different sizes).



Fig. S2. An overview of the used features and the prediction target (root dry weight).



**Fig. S3.** The heatmap of the Pearson correlation coefficient among numerical factors.



**Fig. S4.** The workflow for the establishment of the LightGBM models.



**Fig. S5.** The differences between three nanopriming groups and the control on biological endpoints under salinity stress.



**Fig. S6.** The comparison of biological endpoints among seven treatments in the High group under salinity stress.



**Fig. S7.** The comparison of biological endpoints among selected treatments under combined heat-drought stress.



**Fig. S8.** The superclass of 1204 identified metabolites.



**Fig. S9.** The score plots of PLS-DA of metabolic profiles in maize leaves after SN and SC seed priming in the positive (A) and negative (B) ion modes. The score plots of PLS-DA of metabolic profiles in maize leaves after HdN and HdC seed priming in the positive (C) and negative (D) ion modes.



Fig. S10 (A). The up-regulated and down-regulated metabolites in maize leaves after SN and SC seed priming in the positive ion modes.



**Fig. S10 (B).** The up-regulated and down-regulated metabolites in maize leaves after SN and SC seed priming in the negative ion modes.



**Fig. S11.** KEGG pathway enrichment analysis based on significantly different metabolites between SN and SC.



Fig. S12 (A). The up-regulated and down-regulated metabolites in maize leaves after HdN and HdC seed priming in the positive ion modes.



**Fig. S12 (B).** The up-regulated and down-regulated metabolites in maize leaves after HdN and HdC seed priming in the negative ion modes.



**Fig. S13.** KEGG pathway enrichment analysis based on significantly different metabolites between HdN and HdC.



**Fig. S14.** The absolute values of feature importance obtained by LightGBM feature importance (A), permutation feature importance (B), and SHAP feature importance (C).



**Fig. S15.** The accuracy (A) and F1 score (B) of established models on ten dataset splits.



Fig. S16. PDP and ICE plots of hydrodynamic diameter (A), BET surface area (B),

composition (C), and morphology (D).



composition (C), and morphology (D).



**Fig. S18.** ROC curve of the decision tree (A) and RuleFit (B) models trained on the fifth dataset split.



**Fig. S19.** The decision tree structure for root dry weight prediction based on three important features identified by post hoc interpretation of

LightGBM models.



**Fig. S20.** SHAP interaction values of all features in the decision tree model.



**Fig. S21.** The online interactive website for prediction-level interpretation (https://seednanopriming-isar.streamlit.app/). A, Navigation to different pages on this website. Hello: welcome page. LightGBM: local interpretation in the LightGBM model. Decision tree: local interpretation in the decision tree model. B, Select an instance from the used dataset or customize a sample. C, Dataset introduction and some random instances. D, Show the selected/custom instance and make a prediction. E, Predictionlevel interpretation for this prediction.

### **Tables**



**Table S1.1.** An overview of the used dataset and the prediction target (root dry weight).

**Table S1.2.** Detailed analysis of the numerical features collected in this study.

	<b>TEM</b> size (nm)	<b>TEM</b> size SD(nm)	Concentra tion	Hydrodyn amic	PdI	Zeta potential	<b>BET</b> surface
			(mg/L)	diameter		(mV)	area
				(nm)			(m2/g)
count	224	224	224	224	224	224	224
mean	39.19571	9.621429	93.75	459.0236	0.369286	3.439286	73.07857
std	32.9445	8.734165	67.17389	241.9576	0.215105	20.58079	60.58844
min	12.97	2.65	25	197	0.17	$-32.77$	4.07
25%	17.38	3.11	43.75	264.87	0.22	$-12.93$	25.31
50%	28.685	6.89	75	363.47	0.26	1.595	56.85
75%	42.74	10.98	125	660	0.54	20.63	117.09
max	132.11	32.82	200	933.73	0.81	44.07	200.84

Software/packages	<b>Version</b>		
Python	3.10.8		
scikit-learn	1.1.2		
shap	0.39.0		
PDPbox	0.2.1		
imodels	1.2.5		
lime	0.2.0.1		
scipy	1.7.3		
numpy	1.21.5		
streamlit	1.13.0		
R	4.2.2		
agricolae	$1.3 - 5$		
ropls	1.30.0		

**Table S2.** The version of the main software and packages used in this study.

Random	min data in	min sum hessian	max	max de	num lea	learning
state	leaf	in leaf	bin	pth	ves	rate
	10		5	6	9	0.060
2	10		8	3	4	0.060
3	7		9	4	5	0.067
4			6	4	6	0.049
5		3	14	4	5	0.081
6	15	3	15	4	6	0.064
	17		15	5	7	0.100
8	1	3	15	6	9	0.100
9		3	10	6	9	0.141
10	14		6	4	5	0.074

**Table S3.** The determined model hyperparameters of LightGBM models.

Group	Treatments (Composition: Size(nm) : Concentration(mg/L))	<b>Average SRI</b>	
High $(7)$	ZnO:30:200, CeO <sub>2</sub> : $\leq$ 100:200, SiO <sub>2</sub> :20:50, CeO <sub>2</sub> :20-50:100, SiO <sub>2</sub> :50:50,	11.39	
	$Fe_3O_4:50:100$ , $Fe_3O_4:20:100$		
Middle (16)	CeO <sub>2</sub> : $\leq$ 100:50, $\alpha$ -Fe <sub>2</sub> O <sub>3</sub> :30:100, CuO:40:25, SiO <sub>2</sub> :20:200, ZnO:50:200,		
	SiO <sub>2</sub> :50:100, SiO <sub>2</sub> :50:200, $\alpha$ -Fe <sub>2</sub> O <sub>3</sub> :30:25, CeO <sub>2</sub> :20-50:25, $\alpha$ -Fe <sub>2</sub> O <sub>3</sub> :30:200,	10.74	
	$ZnO:30:50$ , $ZnO:50:50$ , $CuO:40:50$ , $CeO2:20-50:50$ , $ZnO:50:25$ , $SiO2:50:25$		
Low (33)	$SiO_2$ :20:25, Fe <sub>3</sub> O <sub>4</sub> :50:200, CeO <sub>2</sub> :<100:100, SiO <sub>2</sub> :20:100, ZnO:30:25,		
	CeO <sub>2</sub> :20-50:200, CuO:40:200, Fe <sub>3</sub> O <sub>4</sub> :20:50, CuO:50-100:25, $\alpha$ -Fe <sub>2</sub> O <sub>3</sub> :30:50,		
	Fe <sub>3</sub> O <sub>4</sub> :50:25, T <sub>1</sub> O <sub>2</sub> :40:25, T <sub>1</sub> O <sub>2</sub> :20:25, $\gamma$ -Fe <sub>2</sub> O <sub>3</sub> :<50:100, CeO <sub>2</sub> :<100:25,		
	TiO <sub>2</sub> :20:50, TiO <sub>2</sub> :40:100, TiO <sub>2</sub> :40:200, Fe <sub>3</sub> O <sub>4</sub> :20:200, CuO:40:100, $\gamma$ -	9.99	
	$Fe2O3:<50:50$ , $\gamma$ - $Fe2O3:<50:25$ , TiO <sub>2</sub> :20:200, CuO:50-100:50, CuO:50-		
	100:200, ZnO:30:100, CuO:50-100:100, ZnO:50:100, TiO2:40:50,		
	Fe <sub>3</sub> O <sub>4</sub> :20:25, Fe <sub>3</sub> O <sub>4</sub> :50:50, $\gamma$ -Fe <sub>2</sub> O <sub>3</sub> :<50:200, TiO <sub>2</sub> :20:100		

**Table S4.** Three group division of 56 nanopriming treatments based on the SRI under salinity stress.

<b>Ion mode</b>	<b>Type</b>	$R^2X$ (cum)	$R^2Y$ (cum)	$Q^2$ (cum)	<b>Treatments</b>
positive	PLS-DA	0.679	0.994	0.912	SN vs SC
positive	<b>OPLS-DA</b>	0.679	0.994	0.725	SN vs SC
positive	PLS-DA	0.85	0.99	0.895	HdN vs HdC
positive	<b>OPLS-DA</b>	0.85	0.99	0.85	HdN vs HdC
negative	PLS-DA	0.508	0.954	0.744	SN vs SC
negative	<b>OPLS-DA</b>	0.683	0.994	0.87	SN vs SC
negative	PLS-DA	0.769	0.978	0.773	HdN vs HdC
negative	<b>OPLS-DA</b>	0.769	0.978	0.899	HdN vs HdC

**Table S5.** The 7-fold cross-validation results of established PLS-DA and OPLS-DA models.





