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Design Expert Software Being Used to Explore the Factors Affecting the "Water Garden"

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Abstract

The chemical garden experiment demonstrates the formation of plant-like crystal structures using metal salts and sodium silicate. This visually appealing experiment is ideal for chemistry education. In the experiment, metal salt crystals react with sodium silicate, forming membrane structures through osmotic pressure and hydrostatic forces, promoting the growth of silicate structures. Different metal salts produce varied colors and shapes, enhancing the educational value. A study using Design Expert software explored the relationship between metal salt solubility and crystal growth height. Experiments with salts like copper (II) nitrate and iron (III) nitrate showed a linear correlation between solubility and growth height. Higher solubility salts led to taller structures due to sufficient ion supply. The linear regression model confirmed this correlation, with significant statistical results. This study highlights the role of solubility in crystal growth, providing valuable insights for educational purposes. Future research could explore variables like temperature and sodium silicate concentration to deepen understanding of the chemical garden phenomenon. The experiment's basic principle involves the reaction of metal salt crystals with sodium silicate solution, releasing metal ions and forming an insoluble metal silicate membrane. Water molecules enter the membrane through osmotic pressure, increasing the internal liquid volume, causing hydrostatic pressure changes, and promoting the formation and growth of new membranes. The color and surface shape of the metal salts depend on the type of salt used, such as copper salts producing blue, iron salts producing reddish-brown, and cobalt salts producing purple or red structures. The study used nine metal salts, including copper (II) nitrate, iron (III) nitrate, and cobalt (II) nitrate. Each salt has a different solubility, and the experiment measured the crystal growth height. Data analysis showed that higher solubility salts generated taller silicate structures. These findings align with theoretical expectations, where higher solubility salts facilitate rapid membrane formation and upward growth of silicate structures. In summary, the research successfully demonstrated the use of Design Expert software to quantitatively analyze the significant impact of metal salt solubility on crystal growth characteristics. This not only deepens the understanding of the process but also offers practical advice for teachers to reveal the underlying physics in classroom or laboratory activities.

Keywords

Univariate Experiments, Experimental Teaching, Experimental Design

1. Experiment Introduction

The "chemical garden" or "water garden" is a classic demonstration in chemistry education, notable for its striking visual appeal and rich scientific implications. It presents a visually dynamic and chemically rich phenomenon where metal salts react with sodium silicate solution to form vividly colored, plant-like structures. This process provides a pedagogical platform to explore fundamental concepts such as precipitation reactions, osmotic pressure, membrane formation, and self-organization.

Previous research has investigated various aspects of chemical gardens, including their morphological development, dynamics of membrane rupture, and pattern formation [1] [2]. Liu (2006) [3] outlined the specific conditions under which these gardens form, noting the role of ion exchange and osmotic gradients. However, a key factor that has received limited quantitative attention is the solubility of the metal salts involved—a parameter likely to influence both the availability of ions and the rate of membrane formation.

Studies on metal salt solubility have shown its impact on crystallization and membrane growth in related contexts. For instance, Bezerra *et al.* (2008) [4] and Gunst (1996) [5] explored how solubility affects ion transport and precipitation rates in optimization of chemical reactions. Nevertheless, their work did not extend into the specific domain of silicate membrane growth or chemical garden development. Furthermore, response surface methodology [6] [7], has been widely adopted in chemical engineering to model such relationships, but its application to educational experiments like the chemical garden remains relatively unexplored.

This study therefore contributes a novel integration of Design Expert software with a traditional pedagogical experiment, providing a systematic and quantitative assessment of the correlation between metal salt solubility and crystal growth height. By employing linear regression and factorial design methods, the research not only bridges an educational gap—offering students an applied statistical modeling context—but also offers new insights for scientific inquiry into self-organizing chemical systems. Uniquely, this work isolates solubility as a primary factor, analyzes multiple salts with different solubility profiles, and evaluates model robustness through rigorous diagnostics, including ANOVA and residual plots. In doing so, it addresses the existing lack of empirical, software-based modeling in undergraduate-level experiments on chemical gardens.

2. Experiment Overview

The "Underwater Garden" is a classic student lab experiment known for its high safety, engaging visual effects, low cost, and strong aesthetic appeal [3] [8] [9]. It is particularly suitable for first- and second-year chemistry and chemical engineering students as an exploratory experiment.

2.1. Experimental Principle

When solid metal salts are added to a sodium silicate solution, they gradually react to form colored silicate colloids (most silicates are insoluble in water). For example:

$Cu(NO_3)_2 + Na_2SiO_3 = CuSiO_3\downarrow + 2NaNO_{34}$

$MnSO_4 + Na_2SiO_3 = MnSiO_3\downarrow + Na_2SO_4$

$CoCl_2 + Na_2SiO_3 = CoSiO_3\downarrow + 2NaCl$

Metal salt ions readily react with sodium silicate solution to form a silicate membrane. Inside this membrane is a concentrated metal salt solution, while outside is the sodium silicate solution. Due to osmotic pressure, water continuously diffuses into the membrane, leading to the formation of a highly concentrated metal salt solution inside [1].

Since the hydrostatic pressure is lower near the top of the membrane, the upper semi-permeable membrane expands. Once the pressure reaches a critical point, the membrane ruptures, releasing the metal salt solution through the cracks. This solution then reacts with the surrounding sodium silicate, forming a new gel-like metal silicate membrane. This cycle of rupture and reformation repeats, causing the silicate structures to grow upward like branching "stalagmites" until they reach the liquid surface [2].

Moreover, different metal salts produce distinct silicate formations in the sodium silicate solution, resulting in a vibrant and visually striking "chemical garden".

2.2. Experimental Design and Software Introduction

Experimental design involves selecting specific points within a carefully constructed experimental space (composed of potential influencing factors, referred to as "factors")—such as vertices, face centers, centroids, and edge centers—to conduct experiments. Based on the experimental results, statistical principles like variance analysis are applied to establish a functional relationship between the factors and the observed outcomes. This process helps determine the optimal factor conditions that maximize, minimize, or constrain the observed values within a desired range. Some software tools can visually represent the relationship between factors and observed outcomes.

Commonly used experimental design software includes Minitab, Design Expert, and JMP.

This paper presents preliminary results using Design Expert to analyze the factors influencing the length of silicate crystals in the "Underwater Garden" experiment.

2.3. Experimental Reagents and Instruments

1) Sodium silicate

Solid $Cu(NO_3)_2$ Solid $Fe(NO_3)_3$, Solid $Co(NO_3)_2$, Solid $Ni(NO_3)_2$, Solid $Zn(NO_3)_2$, Solid $MnSO_4$, Solid $NiSO_4$, Solid $CuCl_2$, Solid $CoCl_2$.

2) 250 mL beaker, Test tubes, Glass stirring rod, Alcohol lamp, Ruler.

2.4. Experimental Procedure

Approximately 30 g of solid substance is added to a 250 mL beaker, followed by the addition of 100 mL of deionized water. The mixture is gently heated and stirred until fully dissolved. After allowing the solution to stand for 5 minutes, metal salt crystals with diameters of 3 - 5 mm (e.g., copper nitrate, iron nitrate, cobalt nitrate, nickel nitrate, zinc nitrate, manganese sulfate, nickel sulfate, copper chloride, cobalt chloride, etc.) are carefully introduced using tweezers at various positions on the bottom of the beaker containing the sodium silicate (Na_2SiO_3) solution. The time of addition is recorded, and each placement location is clearly marked.

The growth behavior of the metal salts is observed closely, and the length of the resulting structures is measured and recorded at 5-minute intervals. Shortly after introduction, the metal salt crystals begin to develop colorful, plant-like structures—such as blue, brown, purplish-red, yellow, and green formations resembling buds or dendritic "chemical flora".

For long-term preservation of the chemical garden, the sodium silicate solution in the beaker may be carefully removed via siphoning. Subsequently, distilled water is gently added to a glass container, and the beaker is covered with a watch glass to minimize disturbance and evaporation.

3. Experimental Data

A total of 14 students participated in the experiment. The collected data are as follows (Table 1, Table 2):

Table 1. Data for copper (II) nitrate.

	5	10	15	20	25	30	35	40	45	50	55	60
$Cu(NO_3)_2$	1.8	2.6	2.9	2.9	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1
$Fe(NO_3)_3$	3.2	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
$Co(NO_3)_2$	1.9	2.3	2.5	2.7	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
$Ni(NO_3)_2$	2.2	2.4	2.6	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9	2.9
$Zn(NO_3)_2$	0.7	0.9	1.1	1.3	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
$MnSO_4$	0.9	1.5	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6	1.6
$NiSO_4$	0.3	0.3	0.5	0.8	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
$CuCl_2$	1.0	1.1	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
$CoCl_2$	1.2	2.3	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4

Table 2. Solubility data of metal salts used in the experiment.

	Solubility (20˚C, g/100 g H_2O)	Solubility (20˚C, Mol/L)
$Cu(NO_3)_2$	125	3.1
$Fe(NO_3)_3{\cdot}9H_2O$	138 (82.6)	3.6
$Co(NO_3)_2$	97.4	3.0
$Ni(NO_3)_2$	96.3	2.9
$Zn(NO_3)_2$	119	1.4
$MnSO_4$	62.9	1.6
$NiSO_4{\cdot}6H_2O$	44.6 (26.3)	0.9
$CuCl_2$	73	1.4
$CoCl_2$	52.9	2.4

4. Data Processing Procedure

A new single-factor (solubility, 9 levels) and one response variable (height) are designed for a factorial design.

The experimental data are then input into the software for matching analysis.

Table 3. Fitting summary results.

Source	Sequential p-value	Lack-of-fit p-value	Adjusted R^2	Predicted R^2	
Linear	0.0539		0.3522	0.0600	Recommendation
Quadratic	0.9875		0.2443	−0.3200	
Cubic	0.5420		0.1646	−0.6607	
Quartic	0.5659		0.0487	−2.8313	
Quintic	0.3141		0.1460	−57.8784	
Sextic	0.0513		0.8720	−45.9648	Recommendation

As showsn in **Table 3**, Design Expert recommended both the linear model and the sixth-degree model. However, the predicted R^2 for the sixth-degree model is −45.9648, and such higher-degree models are rarely used in practical applications. Therefore, the linear model was selected for further simplification, followed by analysis of variance (ANOVA).

Table 4. ANOVA for the first linear model.

Source	Variance Summary	df	Mean Square	F-value	p-value	
Model	3.14	1	3.14	5.35	0.0539	Not Significant
A-A	3.14	1	3.14	5.35	0.0539	
Residual	4.10	7	0.5864			
Total Corrected	7.24	8				

The linear model is not significant. According to statistical principles, a model is considered significant when the p-value is less than 0.0001. Additionally, the variance summary shows that the model can only predict 43.37% of the total corrected variance (3.14/7.24), with an accuracy of less than 50%.

Therefore, this linear model is not significant.

Further analysis of the experimental content revealed that among the nine salts, only zinc nitrate is colorless, while the other eight salts in the chemical garden experiment showed distinct colors in water. It is therefore preliminarily considered that colorless metal salts should be excluded. The data is then refitted (**Table 4**).

Table 5. Fitting summary for the second linear fit.

Source	Sequential p-value	Lack-of-fit p-value	Adjusted R^2	Predicted R^2	
Linear	0.0057		0.7033	0.5623	Recommendation
Quadratic	0.7983		0.6491	0.4327	
Cubic	0.8583		0.5653	−0.3122	
Quartic	0.9219		0.4226	−26.8867	
Quintic	0.0232		0.9603	−84.9654	Recommendation
Sextic	0.1298		0.9967	−135.3958	

The linear model was selected as shown in **Table 5**.

Table 6. ANOVA for the second linear model.

Source	Variance Summary	df	Mean Square	F-value	p-value	
Model	4.79	1	4.79	17.59	0.0057	Significant
A-A	4.79	1	4.79	17.59	0.0057	
Residual	1.63	6	0.2720			
Total Corrected	6.42	7				

The model is effective. The solubility of various salts has a significant impact on the crystal growth height (**Table 6**).

Table 7. Statistical parameters for the second linear model.

Std. Dev.	0.5216	R^2	0.7457
Mean	2.36	Adjusted R^2	0.7033
C.V. %	22.08	Predicted R^2	0.5623
		Adeq Precision	8.7753

Conclusion: The model is effective. The difference between the Adjusted R^2 (0.7033) and the Predicted R^2 (0.5623) is less than 0.2, and the R^2 value (0.7457) is also considered acceptable.

According to the software's fitting results, the recommended linear regression equation is as follows Table 7.

$R_1 = +0.248873 + 0.024502A$

Where A represents the solubility of the chemical substance (g/100 mL water).

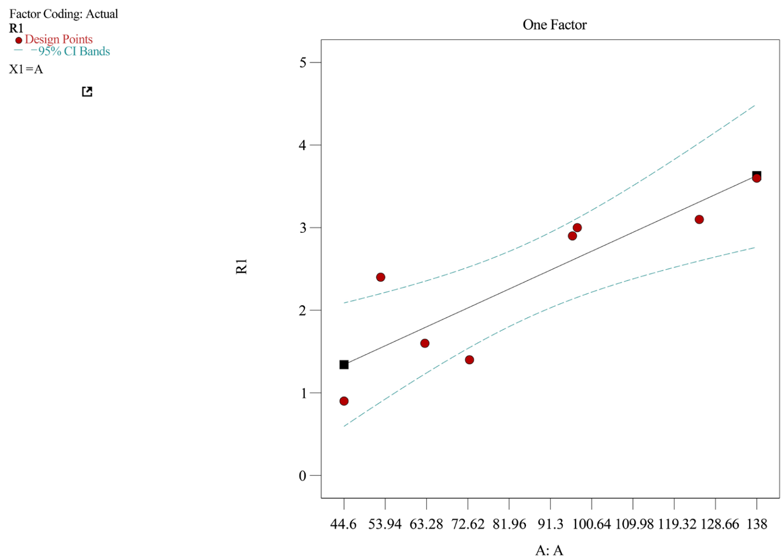

Figure 1. Diagnostic plots for the second linear fit.

Top Left: Normal probability plot of residuals—the data fits the model well.

Bottom Left: Box-Cox plot—no transformation of the data is required.

Top Right: Residuals vs. predicted values—no outliers are observed.

Bottom Right: Cook's distance plot—no influential data points are detected (Figure 1).

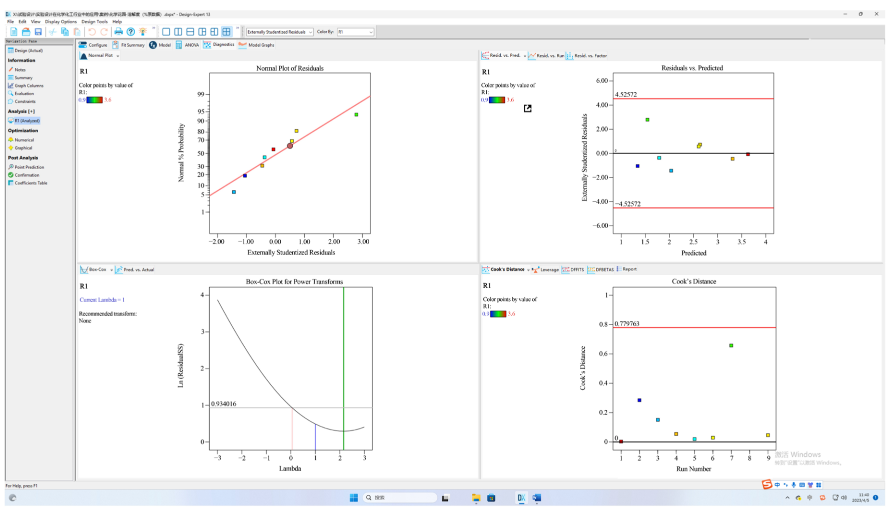

Figure 2. Main effect plot after the second fitting.

There is a clear linear relationship between solubility and growth height (**Figure 2**).

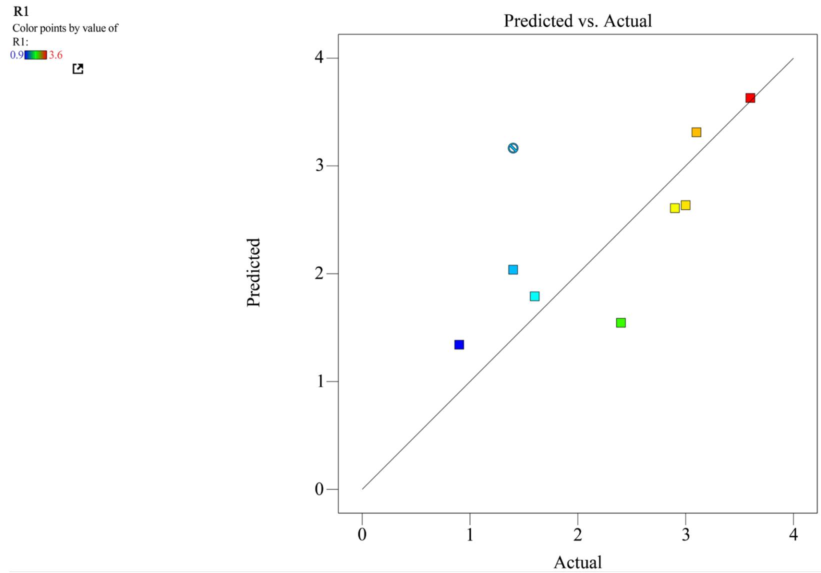

Figure 3. Predicted vs. Actual values after the second fitting.

There is a good agreement between the predicted and actual values. Note that the data point in the upper left corner of the plot corresponds to zinc nitrate, which was previously excluded. This data point is clearly inconsistent with the rest of the dataset [6] [7] [10] [11] (**Figure 3**).

5. Analysis and Discussion

Using Design Expert to analyze the factors affecting crystal length in the chemical garden experiment, it was found that the solubility of various salts has a significant impact on the crystal growth height. This is consistent with the principles of the "chemical garden" [12].

Therefore, the plan is to continue guiding students to use Design Expert software for a comprehensive analysis and discussion of the factors affecting crystal growth height in the "chemical garden", including (1) temperature, (2) the concentration of sodium metasilicate solution, and (3) the modulus of sodium metasilicate [5].

The findings of this study—particularly the statistically validated correlation between metal salt solubility and crystal growth height—can be directly leveraged to enhance educational practices in chemistry and chemical engineering courses. Below are several proposed changes to pedagogical methods that incorporate the study's outcomes:

5.1. Integrate Quantitative Modeling into Introductory Laboratory Courses

Traditionally, chemical garden experiments are presented as qualitative demonstrations. This study suggests redesigning the lab to include quantitative components, where students collect growth data and use software such as *Design Expert* or *Excel* to fit linear models. This fosters a deeper understanding of variable control and experimental reproducibility.

5.2. Introduce Concepts of Statistical Analysis Early in Curriculum

By incorporating ANOVA, regression analysis, and residual diagnostics into first- or second-year chemistry labs, students can begin developing essential data analysis skills early. This also strengthens cross-disciplinary links with statistics and engineering.

5.3. Use Solubility-Dependent Growth to Teach Predictive Thinking

Teachers can pose pre-lab hypotheses such as: Which salt will produce the tallest structure? Why? Students can then test these predictions experimentally and validate them against solubility tables, reinforcing the link between theoretical chemistry and experimental outcomes.

5.4. Develop Scaffolded Learning Module

This experiment can be expanded into a multi-week module:
* **Week 1**: Introduction to chemical garden formation and basic qualitative observations.
* **Week 2**: Data collection from multiple salts and introduction to solubility.
* **Week 3**: Statistical modeling using collected data.
* **Week 4**: Discussion of model validity and real-world implications.

5.5. Encourage Design of Controlled Experiments by Students

Based on this study's framework, students can be guided to design their own variants—e.g., changing temperature, Na_2SiO_3 concentration, or using different metal ions—to investigate how these variables affect growth. This shift from "cookbook" procedures to inquiry-based experimentation promotes scientific curiosity and ownership of learning.

5.6. Use the Experiment as a Gateway to Interdisciplinary Topics

The chemical garden can serve as a springboard to introduce topics such as biomimicry (growth patterns similar to biological forms), environmental chemistry (mineralization processes), or materials science (membrane formation and structure).

6. Conclusion

Analysis using Design Expert software confirms that there is a linear relationship between the growth height of crystals in the chemical garden and the solubility of the corresponding substances [4].

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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