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Life Assessment of Protective Coatings for Copper Alloy Relics via a Hybrid Finite Element Modeling and Spatiotemporal Deep Learning Approach

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Abstract

Bronze and copper alloy cultural relics are exceptionally susceptible to localized corrosion and "bronze disease" in chloride-containing burial environments, thereby posing a severe threat to their structural integrity and historical information integrity. Addressing the inherent limitations of conventional corrosion evaluation methods, which are characterized by protracted cycles, destructiveness, and difficulty in achieving long-term trend predictions, this study constructs a novel intelligent assessment framework for protective coating service life by fusing Finite Element Modeling (FEM) with spatiotemporal deep learning. Utilizing nickel-aluminum bronze (NAB) as a model alloy, a two-dimensional localized corrosion model was established based on electrochemical kinetics and the Nernst-Planck equation to systematically simulate the interface evolution process of four distinct protective systems within a 1200-hour service cycle. Consequently, a spatiotemporal dataset containing 4800 sequential images was constructed. On this foundation, three typical spatiotemporal prediction models—GRU, ConvLSTM, and PredRNN—were introduced to train and validate the dynamic evolution rules of the corrosion interface. The results demonstrate that all three models can successfully capture the spatiotemporal coupling characteristics of the corrosion process. Among them, ConvLSTM exhibited remarkable performance owing to the strong capability of its convolutional structure to extract localized spatial features, achieving a Mean Squared Error (*MSE*) as low as 3.0×10^{-6} , and Structural Similarity Index (*SSIM*) and Peak Signal-to-Noise Ratio (*PSNR*) of 0.9997 and 55.71 dB, respectively, on the validation set, while maintaining remarkable high-consistency interface structural fidelity even in long-term prediction. This study confirms that the proposed FEM-deep learning synergistic strategy enables rapid, non-destructive, and high-precision prediction of the corrosion state of copper alloy cultural relics, providing reliable theoretical basis and technical support for protective coating service life assessment, preventive conservation strategy formulation, and scientific maintenance decision-making.

Keywords: Copper alloy cultural relics; Protective coatings; Finite Element Modeling; Deep learning; Corrosion prediction

1. Introduction

Bronzes, as materials carrying milestone significance in the history of human civilization, bear multi-dimensional precious information such as smelting technology, artistic aesthetics, and ritual systems of ancient societies (Cofini et al. 2025; K. Chen et al. 2009; Rosenberg and Chasan 2018; X.-X. Chen et al. 2018). However, having endured millennia of fluctuations within their burial and host environments, the vast majority of excavated bronzes face severe threats of corrosion and degradation, typified by the notorious "bronze disease" (Cofini et al. 2025; W. Liu 2025; Li et al. 2025; Sandu et al. 2008). Although many treatment and preservation techniques have been developed that delay the corrosion process to some extent, the corrosion process is insidious, sudden, and irreversible; post-hoc interventions are often unable to reverse existing corrosion damage, still constituting a major risk to the long-term preservation of the relics (W. Liu 2025; J. Wu et al. 2026; Cao et al. 2024; W. Wu et al. 2024). Therefore, developing scientific and reliable corrosion process prediction methods to achieve forward-looking assessment of bronze corrosion risk and evolution trends has important practical implications and academic value: on one hand, it can provide key basis for formulating preventive conservation strategies, pushing relic management from passive restoration to active early warning, thereby maximizing their survival lifespan; on the other hand, it can also promote the development of cross-disciplinary fields such as environmental corrosion modeling and cultural heritage preventive conservation (Kwon and Cho 2024; J. Wu et al. 2026; Q. Zhu et al. 2026).

However, current bronze corrosion prediction still faces severe challenges such as data scarcity, unclear multi-factor coupling mechanisms, insufficient model generalization ability, and difficulty in verifying long-term accuracy (Roqui et al. 2025; Yang et al. 2020). Any prediction method suitable for precious relics must adhere to the

fundamental principle of "minimal intervention" and "non-destructive testing" (Zhang et al. 2024). Reviewing existing technologies against this benchmark: traditional corrosion evaluation methods, such as salt spray tests, weight loss analysis, and cross-sectional observation, often cause irreversible damage to samples, making them difficult to directly apply to precious relics (Kwon and Cho 2024; X. Wang et al. 2024). Electrochemical Impedance Spectroscopy (EIS), as a common non-destructive testing technology, can reflect protective performance, but its testing process is complex and it struggles to visually display the dynamic evolution of the corrosion interface (Angelini et al. 2010). The aforementioned methods only detect the current degree of corrosion and cannot predict the corrosion process, especially long-term corrosion behavior. FEM, although able to quantitatively describe corrosion interface evolution by coupling electrochemical kinetics and mass transfer processes, involves high computational costs as simulation time extends and model complexity increases, limiting its application in long-term corrosion prediction (Katona et al. 2024; C. Liu and Kelly 2019; Q. Zhu et al. 2026).

In recent years, the development of machine learning has brought new ideas to solving the problem of long-term corrosion prediction (Qi et al. 2025). Deep learning technologies have achieved significant progress in the field of spatiotemporal sequence prediction (Hosseini et al. 2025). Among them, ConvLSTM achieves synergistic modeling of spatial and temporal information by introducing convolutional operations into Long Short-Term Memory networks; PredRNN further introduces a dual-flow memory transfer mechanism, enabling it to capture long-term dependencies in complex spatiotemporal evolution more effectively (Shi et al. 2015; Y. Wang et al. 2023). Methods combining FEM and deep learning have demonstrated considerable prospects in material performance prediction and corrosion behavior analysis (Sahlmann et al. 2026; Gollé-Leidreiter et al., n.d.; Sun et al. 2024). However, there is still a lack of systematic exploration regarding how to establish a hybrid model merging FEM prior knowledge and deep learning data-driven capabilities specifically for bronze relics.

Addressing this research gap and considering the difficulty in obtaining real relic corrosion data and its non-destructive nature, this study selects NAB, which has corrosion mechanisms close to ancient bronzes, as a model alloy to construct a corrosion prediction framework fusing FEM and deep learning (**Figure 1**). First, a two-dimensional FEM is established based on electrochemical kinetics and the Nernst-Planck equation to simulate the interface corrosion evolution process of NAB alloy under different protective systems, generating a corrosion dataset containing a large number of images. Subsequently, typical spatiotemporal prediction models such as GRU, ConvLSTM, and PredRNN are employed to learn and predict the evolution rules of the corrosion interface, systematically comparing the performance differences of each model in corrosion morphology reconstruction and long-term prediction. The results show that the spatiotemporal models incorporating spatial convolutional structures significantly enhance corrosion interface prediction accuracy and structural maintenance capability, with ConvLSTM outperforming GRU and PredRNN across *MSE*, *SSIM* and *PSNR* metrics, exhibiting the best overall performance. This study aims to develop a rapid corrosion process prediction framework for bronze relics, providing theoretical basis and technical support for relic preventive conservation, coating optimization design, and maintenance strategy formulation.

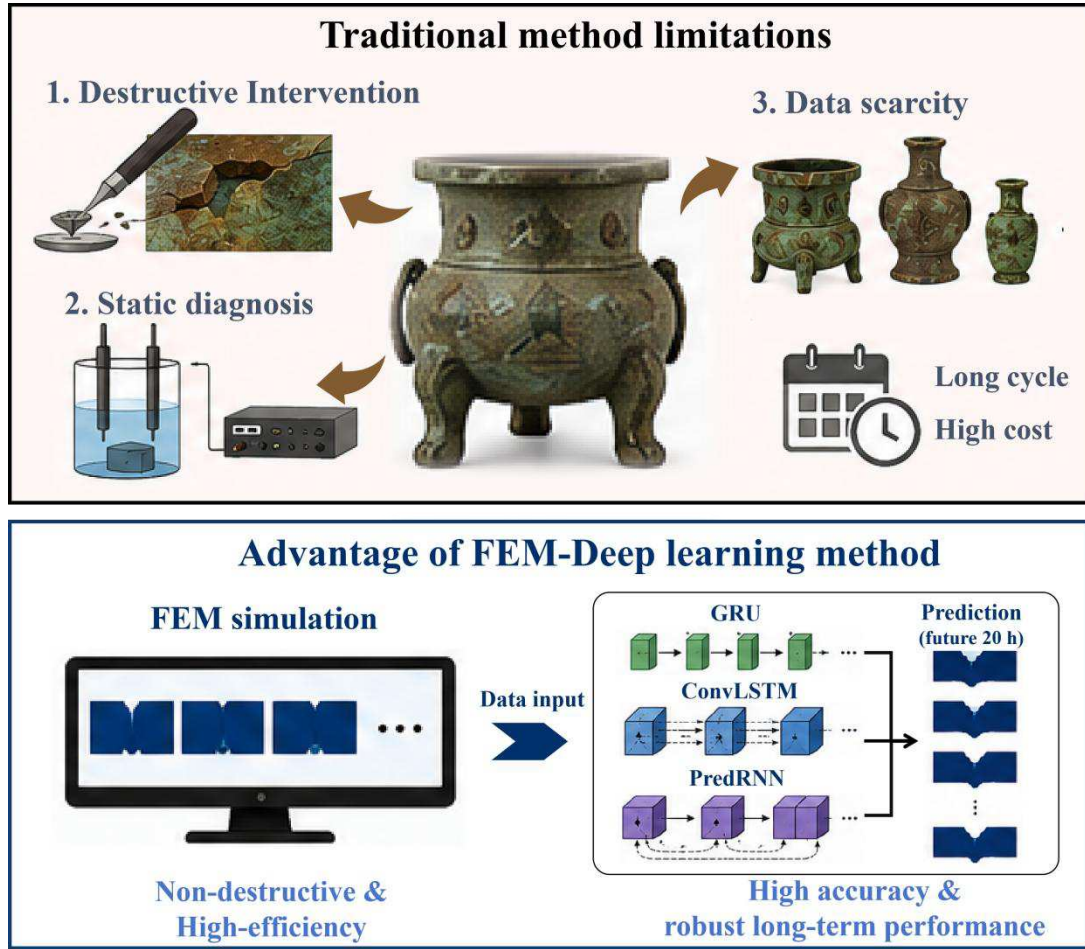


Figure 1. Schematic comparison between the limitations of traditional corrosion assessment methods and the advantages of the proposed FEM-deep learning framework. (Top) Traditional assessment approaches for bronze artifacts are intrinsically hindered by destructive interventions, static diagnosis, and severe data scarcity, which are typically accompanied by prolonged experimental cycles and prohibitive costs. (Bottom) The proposed paradigm overcomes these bottlenecks by utilizing FEM to non-destructively and efficiently generate large-scale corrosion evolution datasets. These datasets serve as inputs for advanced spatiotemporal deep learning networks (GRU, ConvLSTM, and PredRNN) to predict future interfacial morphology (forecasting the next 20 h), demonstrating remarkably high accuracy and robust long-term predictive performance for preventive conservation.

2. Methods

2.1 Finite Element Modeling

COMSOL Multiphysics was employed to establish a two-dimensional localized corrosion model for the NAB protective system, aiming to study the spatiotemporal evolution behavior of the corrosion interface under different coating conditions. The

geometric dimensions of the model were $140\text{ }\mu\text{m} \times 50\text{ }\mu\text{m}$, with a protective coating of $1\text{ }\mu\text{m}$ thickness covering the surface (**Figure 2a**). To simulate localized corrosion induced by coating defects during actual service, a micro-crack with a width of $1\text{ }\mu\text{m}$ was pre-set on the coating surface as the initiation site for corrosion. The corrosion process of copper alloys in chloride-containing environments mainly includes the anodic metal dissolution reaction and the cathodic oxygen reduction reaction. This study focuses on the impact of different protective systems on overall corrosion behavior; therefore, experimentally measured polarization curves were used to directly characterize the interface electrochemical reaction kinetics. The polarization curves of the four protective systems were derived from electrochemical experimental test results (**Figure 2b-f**) and imported into the model as interpolation functions to serve as boundary conditions, thereby establishing the correspondence between electrode potential and localized current density (Jain 2026; H. Wang et al. 2020; W. Wu et al. 2025).

To simulate the chloride-containing corrosion environment common to copper alloy cultural relics, the electrolyte conductivity was set to 2.5 S m^{-1} . The ion transfer process in the electrolyte was described using the Nernst-Planck equation:

$$N_i = -D_i \nabla c_i - z_i F u_i c_i \nabla \varphi + c_i U$$

where N_i is the ion flux, D_i is the diffusion coefficient, c_i is the ion concentration, z_i is the ion charge number, u_i is the ion mobility, F is the Faraday constant, φ is the electric potential, and U is the fluid velocity. Considering that the electrolyte is basically in a stationary state under the conservation environment of relics and experimental conditions, the convection effect brought by macroscopic fluid flow was ignored, and only the effects of diffusion and electromigration on ion transport were considered. At the same time, it was assumed that the electrolyte is uniformly distributed, the temperature remains constant, and the effects of gas evolution, corrosion product shedding, and environmental parameter fluctuations on the corrosion process were not considered.

The evolution of the corrosion interface is driven by localized current density, and the interface movement rate was calculated according to Faraday's law. The Arbitrary Lagrangian-Eulerian (ALE) moving mesh method was employed to achieve dynamic updates of the solid-liquid interface, thereby obtaining interface morphology changes at different corrosion stages. All simulations utilized a transient solver, combined with an adaptive time-stepping and automatic mesh remeshing strategy to ensure numerical stability. As the corrosion process progressed, the solver automatically adjusted the time step according to the interface change rate, and each system usually achieved stable convergence within 50–120 time steps. Continuous corrosion evolution results for the four protective systems within a 1200-hour service cycle were ultimately obtained, to be used for subsequent deep learning model dataset construction and spatiotemporal prediction analysis.

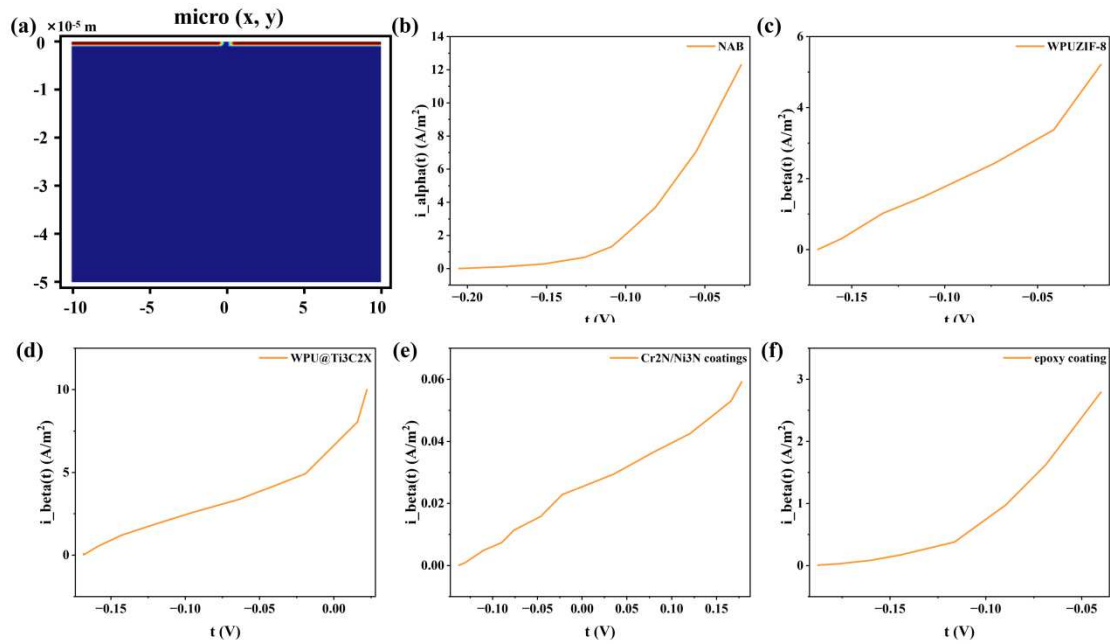


Figure 2. (a) The microstructure of NAB-based pitting corrosion model. Polarization curve of (b) NAB alloy, (c) WPU@ZIF-8, (d) WPU@Ti₃C₂X, (e) Cr₂N/Ni₃N and (f) Epoxy.

2.2 Dataset Construction

Continuous simulation of the corrosion behavior of NAB under different protective systems was conducted based on the FEM, with a total simulation duration

of 1200 hours. To obtain corrosion evolution data with temporal continuity, the interface morphology was output at intervals of 1 hour. For the four protective systems, WPU@ZIF-8, WPU@Ti₃C₂X, Cr₂N/Ni₃N, and Epoxy, 1200 corrosion evolution images were obtained for each, constructing a dataset containing a total of 4800 images.

To meet the input requirements of deep learning models for temporal data, a sliding time window method was used to construct sample sequences. Each sample consists of corrosion morphology images from 10 consecutive time steps, used to predict the interface evolution process for the next 20 time steps. Sliding the window effectively expands the number of training samples, enhancing the model's ability to learn the dynamic corrosion process. All images underwent uniform size adjustment and normalization before being input into the network to eliminate the influence of different data scales on model training. The dataset was first divided into a training set and a test set at a ratio of 8:2, with the test set used only for final model performance evaluation. Subsequently, the training set was further divided into a training subset and a validation subset at a ratio of 8:2: the training subset was used for model parameter optimization, and the validation subset was used for monitoring model convergence and performing hyperparameter adjustment to improve the model's generalization ability and prediction stability.

2.3 Deep Learning Models and Evaluation Metrics

The evolution of the corrosion interface is manifested not only as cumulative effects in the time dimension but is also accompanied by continuous changes in spatial morphology; therefore, this study treats it as a typical spatiotemporal sequence prediction problem. To compare the learning capabilities of different network structures regarding corrosion evolution rules, three representative models—GRU, ConvLSTM, and PredRNN—were selected for analysis.

GRU is a classic recurrent neural network structure that achieves dynamic transfer of historical information through update gates and reset gates, effectively learning long-

term dependencies in time series. ConvLSTM introduces convolutional operations into the traditional LSTM structure, replacing fully connected layers with convolutional units, enabling the model to extract spatial and temporal features simultaneously, suitable for dynamic image sequence prediction tasks. PredRNN further introduces spatiotemporal long short-term memory units and a dual-flow memory transfer mechanism, enhancing the model's representation capability for complex spatiotemporal dynamic processes and improving memory transfer efficiency in long sequence predictions. The three models represent methods of time series modeling, spatiotemporal joint modeling, and enhanced spatiotemporal memory modeling, respectively. By comparing their prediction results, the learning capability of different network structures regarding corrosion interface evolution rules can be evaluated. All models were trained using the Adam optimizer, with an initial learning rate set to 0.001, training epochs set to 100, and batch size set to 4.

To quantitatively evaluate model prediction performance, *MSE*, *SSIM*, and *PSNR* were used as evaluation metrics (Horé and Ziou 2010).

MSE is defined as:

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

where y_i and $\hat{y}_i$ represent the true value and predicted value, respectively.

SSIM is defined as:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

where x and y represent the true image and predicted image, respectively, μ_x and μ_y represent image means, σ_x and σ_y represent standard deviations, σ_{xy} represents covariance, and c_1 and c_2 are stabilization constants. *SSIM* is used to evaluate the similarity between the predicted image and the true image in luminance, contrast, and structural information; its value ranges closer to 1, indicating the predicted result is closer to the true image.

PSNR is defined as:

$$PSNR = 10 \log_{10} \frac{MAX^2}{MSE}$$

where *MAX* is the maximum pixel value of the image. A higher *PSNR* indicates higher consistency between the predicted image and the true image, and better predicted image quality.

3. Results and Discussion

3.1 Finite Element Modeling and Corrosion Evolution Analysis

In order to obtain high-quality spatiotemporal evolution data suitable for deep learning training, numerical simulations of the long-term corrosion behavior of NAB alloy under different protective systems were first conducted using the FEM. **Figure 3** displays the dynamic changes of the adaptive time step during the transient solution process for the four coating systems. It can be observed that in the initial stage of simulation, the adaptive time step decreases rapidly, subsequently gradually tending towards a constant value. This trend indicates that the established numerical model possesses good numerical stability and convergence performance, capable of reliably capturing the evolution process of the corrosion interface.

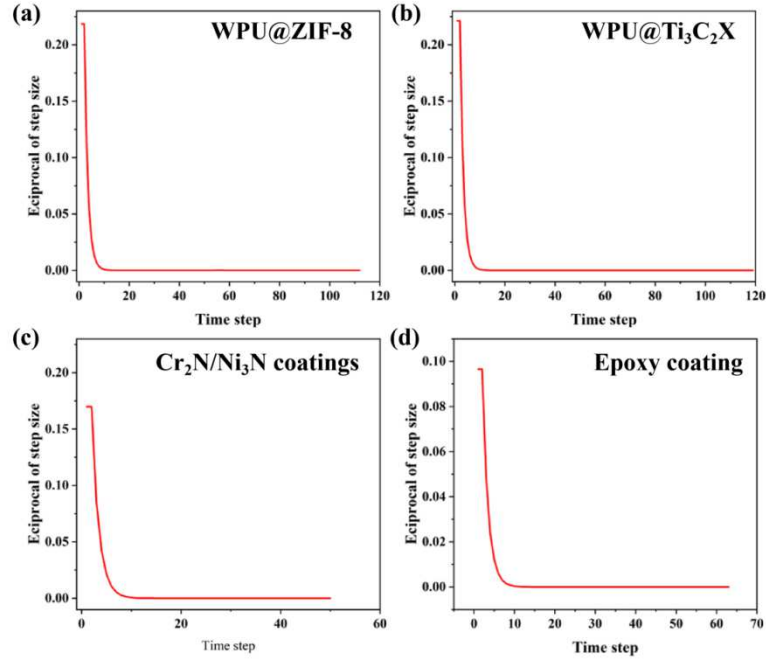


Figure 3. Convergence behavior of the FEM model during corrosion simulation under different coating systems.

Figure 4a further provides the corrosion evolution results for the four protective systems, WPU@ZIF-8, WPU@Ti₃C₂X, Cr₂N/Ni₃N, and Epoxy, within the service cycle from 0 to 1200 hours. Overall, with the extension of corrosion time, the coating defect regions gradually induce the formation of localized pitting corrosion pits, continuously expanding along the longitudinal (depth) and transverse (surface) directions. However, significant differences exist in the inhibition capability of different protective systems against corrosion behavior. Among them, the Cr₂N/Ni₃N system exhibits the slowest corrosion expansion rate, with the development of pitting pits distinctly limited. In contrast, the WPU@ZIF-8 and WPU@Ti₃C₂X systems show more obvious pitting pit deepening phenomena during long-term service, indicating that their protective performance degrades under long-time exposure. The corrosion behavior of the Epoxy system falls between the aforementioned two, presenting a moderate degree of protective effect. In summary, the established FEM can reasonably reproduce the corrosion behavior of NAB alloy under different protective systems and generate corrosion evolution data with continuous spatiotemporal characteristics. These high-

fidelity simulation results provide a reliable data foundation for the subsequent training and validation of deep learning models.

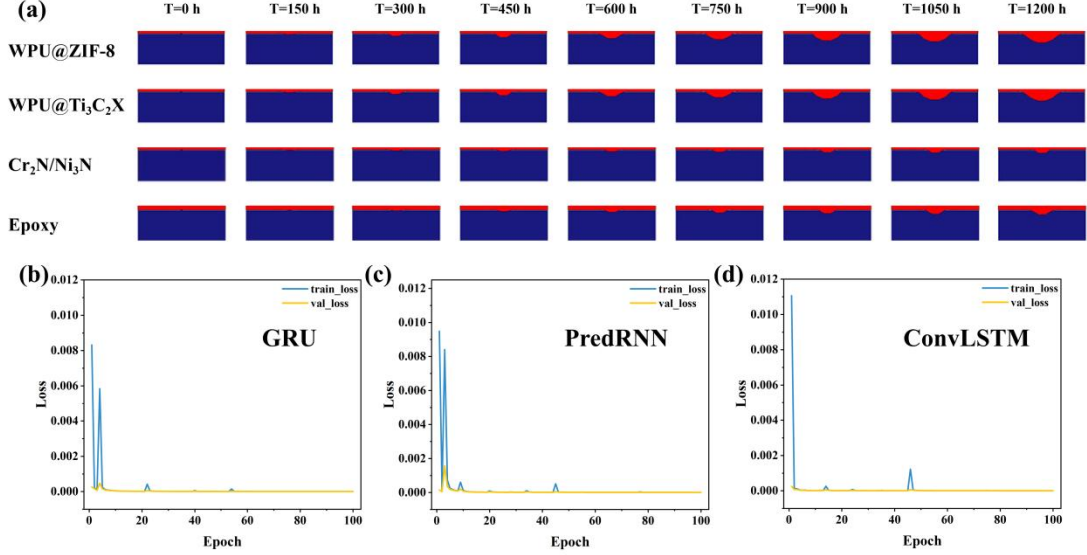


Figure 4. (a) FEM-simulated corrosion evolution of NAB alloy protected by WPU@ZIF-8, WPU@Ti₃C₂X, Cr₂N/Ni₃N and Epoxy coatings from 0 to 1200 h. Training and validation loss curves of (b) GRU, (c) PredRNN and (d) ConvLSTM models during the learning process.

3.2 Deep Learning Model Training

Figure 4b-d displays the changes in Train Loss and Validation Loss for the GRU, ConvLSTM, and PredRNN models during the training process. All three models show a rapid decline trend in the early stage of training, stabilizing after approximately 20 epochs, indicating that the dataset can effectively support model training, and no severe overfitting phenomenon was observed throughout the process. From the convergence behavior, ConvLSTM exhibits the fastest convergence speed and the smoothest validation loss curve, attributed to its convolutional structure effectively extracting localized spatial features of the corrosion interface, thereby accelerating the learning of spatiotemporal correlations; in comparison, although GRU has a faster convergence speed, it lacks spatial processing capability, resulting in limitations in interface reconstruction. PredRNN converges more slowly in the initial stage of training due to its dual-flow memory structure increasing model complexity; however, the loss

gradually stabilizes in the later stage of training, suggesting theoretically that it still possesses potential in long-sequence spatiotemporal modeling, but subsequent quantitative results will show its actual gain is limited.

Furthermore, **Table 1** provides the quantitative evaluation results for the three models on the training set, validation set, and test set. The *MSE* metric shows that all three models can accurately learn the overall evolution trend of the corrosion interface. Further analysis of *SSIM* and *PSNR* results reveals that ConvLSTM achieves the highest values, with its validation set *SSIM* and *PSNR* being 0.9997 and 55.71 dB, respectively, indicating its optimal performance in pitting pit boundary continuity and structural maintenance capability. PredRNN is slightly lower than ConvLSTM across some metrics, suggesting that its complex spatiotemporal memory mechanism did not bring significant additional advantages under this dataset. GRU, due to its lack of spatial feature extraction capability, has *SSIM* and *PSNR* values lower than both spatiotemporal models, revealing its distinct limitations in interface morphology reconstruction (L. Zhu et al. 2024; Brum et al. 2026). In summary, for corrosion interface evolution, which is a typical spatiotemporal coupling problem, incorporating spatial convolutional structures is a key factor in improving prediction accuracy and maintaining interface structural consistency, and ConvLSTM demonstrates the best overall performance under the data and task conditions of this study.

Table 1. The evaluation metrics of the deep learning model.

Data	Model	<i>MSE</i>	<i>SSIM</i>	<i>PSNR</i>
Training Set	ConvLSTM	3.00×10^{-6}	0.9996	55.71
	PredRNN	4.00×10^{-6}	0.9996	54.21
	GRU	4.00×10^{-6}	0.9995	54.47
Validation Set	ConvLSTM	3.00×10^{-6}	0.9997	55.71
	PredRNN	4.00×10^{-6}	0.9996	54.12
	GRU	4.00×10^{-6}	0.9995	54.46

3.3 Long-term Prediction of Interface Corrosion State

To evaluate the long-term prediction capability of different models, the corrosion morphology sequence from 1024–1033 h in the test set was selected as input to predict the interface evolution process during 1034–1053 h. **Figure 5a** takes the WPU@ZIF-8 system as an example to display the comparison between prediction results and the true interface (results for other systems are in **Figures 6a, 7a, 8a**). From Figure 5a, it is visible that all three models can reasonably reproduce the overall migration trend of the corrosion interface, but significant differences exist in localized structure maintenance capability. To quantify these differences in the specific performance of long-term prediction, **Figures 5-8** further provide the sequential changes of *MSE*, *SSIM*, and *PSNR* for different systems during the prediction process. Among them, ConvLSTM consistently maintains the lowest *MSE* and the highest *SSIM* and *PSNR* values, indicating its prediction results have the highest consistency with the true state. In comparison, the performance of PredRNN is slightly inferior to ConvLSTM but still distinctly superior to GRU. Although GRU can effectively capture evolution rules in the time dimension, it faces obvious bottlenecks in interface structure maintenance due to its lack of explicit modeling of spatial features.

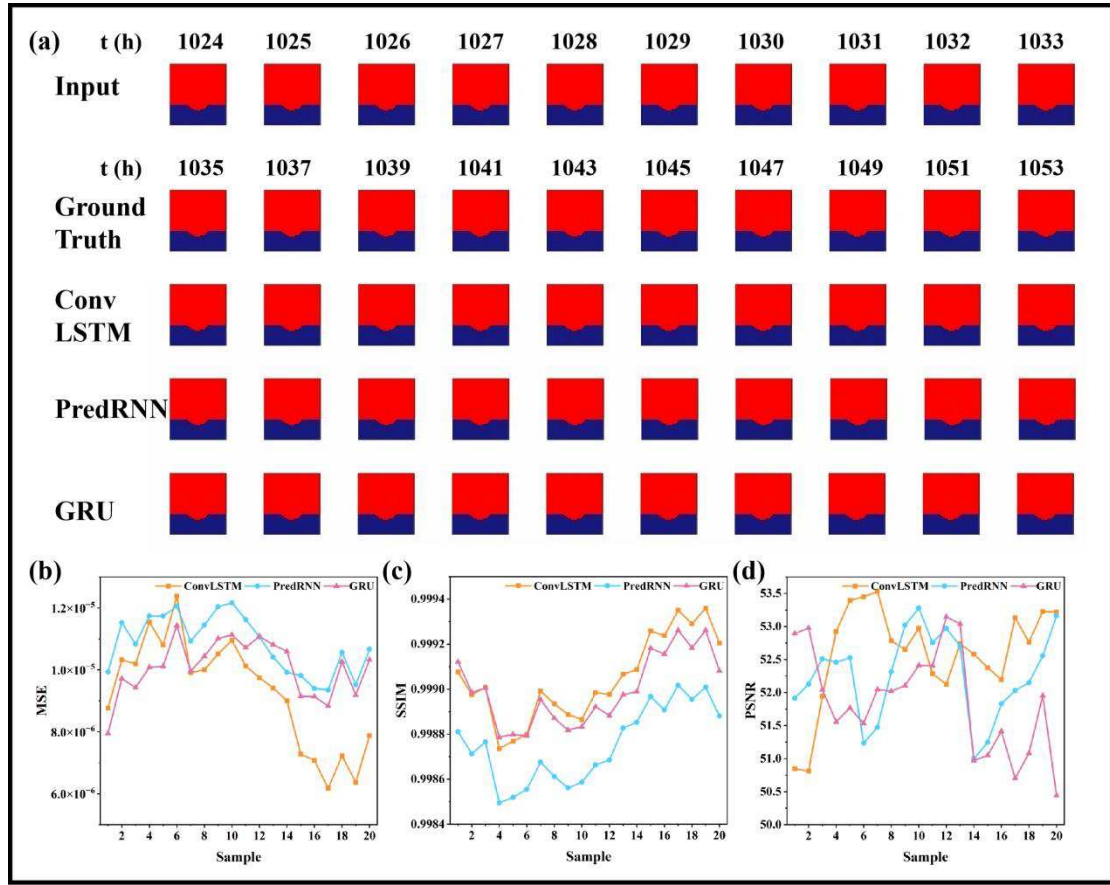


Figure 5. (a) Qualitative comparison of GRU, PredRNN and ConvLSTM predictions for corrosion images of a test sample (WPU@ZIF-8). Single frame evaluation metrics (b) *MSE*, (c) *SSIM*, (d) *PSNR* curve (WPU@ZIF-8) for GRU, PredRNN and ConvLSTM model.

The aforementioned comparisons indicate that corrosion interface evolution not only possesses temporal continuity but is accompanied by significant spatial structural transformations. Therefore, compared to GRU, which focuses only on time dependence, ConvLSTM and PredRNN, fusing spatiotemporal joint modeling, can more fully extract interface dynamic features. Notably, although PredRNN designed a more complex memory mechanism, its gain in this dataset was limited; whereas ConvLSTM, relying on a concise convolutional structure, achieved the best balance among prediction accuracy, structural fidelity, and long-term stability. In summary, ConvLSTM possesses higher engineering applicability for the failure process prediction and life assessment of copper alloy relic protective coatings.

Given its superior prediction performance, the proposed FEM–deep learning

framework has considerable potential for practical applications in cultural heritage conservation. Because copper alloy relics are precious and non-renewable, traditional corrosion assessment methods still suffer from three major limitations: (1) **Destructive intervention:** Microscopic and phase characterization rely on sampling, violating the principle of "minimal intervention"; (2) **Lack of foresight:** Electrochemical tests are mostly static post-hoc diagnoses, unable to predict long-term dynamic evolution; (3) **Data scarcity:** Pure data-driven models are restricted by the scarcity of relic samples, making them difficult to implement. This study innovatively fuses FEM and spatiotemporal deep learning, upgrading corrosion detection from "static recognition" to "dynamic prediction". This method utilizes physical models to generate massive evolution data, completely circumventing physical damage to real relics; simultaneously relying on models like ConvLSTM, it predicts interface evolution trends for long future cycles with extremely high structural fidelity. This work not only overcomes the limitations imposed by limited corrosion data for long-term corrosion prediction but also provides non-destructive, efficient digital support for the scientific optimization, life quantitative assessment, and active maintenance cycle formulation of museum bronze protective coatings, holding important significance for the preventive conservation of cultural heritage.

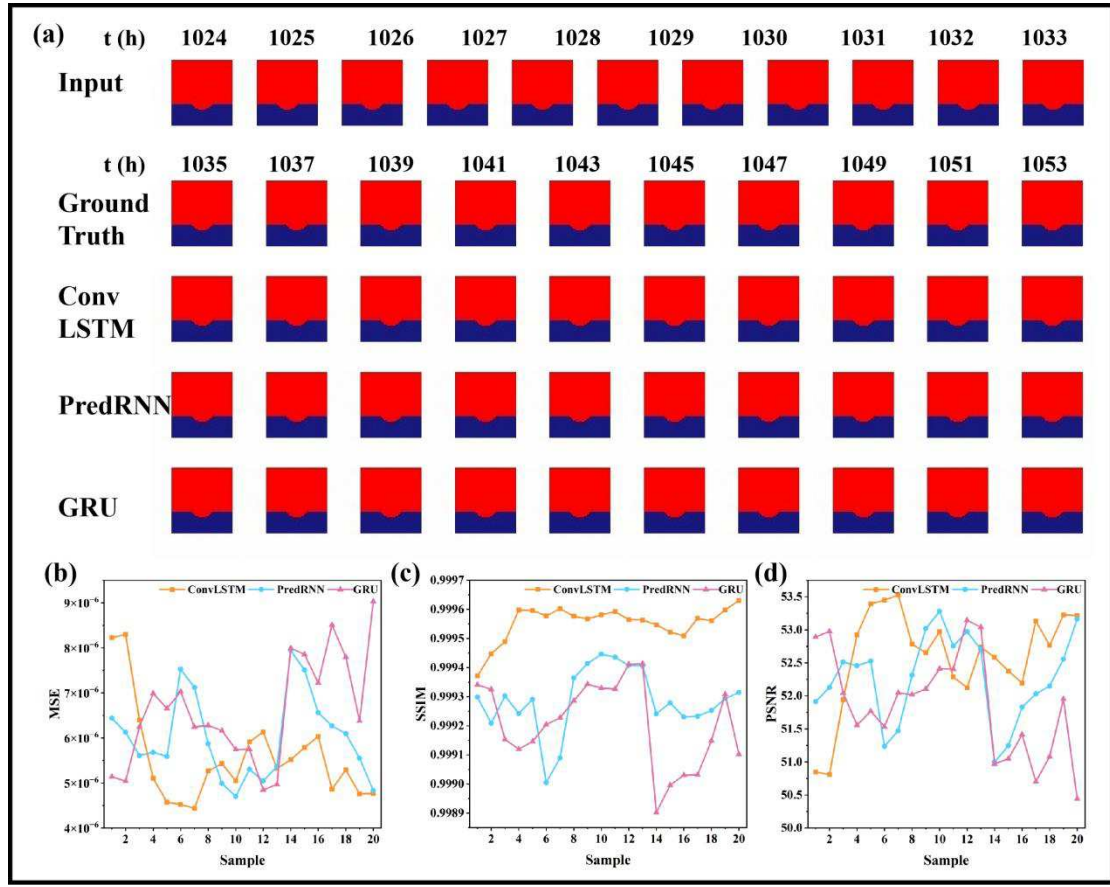


Figure 6. (a) Qualitative comparison of GRU, PredRNN and ConvLSTM predictions for corrosion images of a test sample (WPU@Ti₃C₂X). Single frame evaluation metrics (b) *MSE*, (c) *SSIM*, (d) *PSNR* curve (WPU@Ti₃C₂X) for GRU, PredRNN and ConvLSTM model.

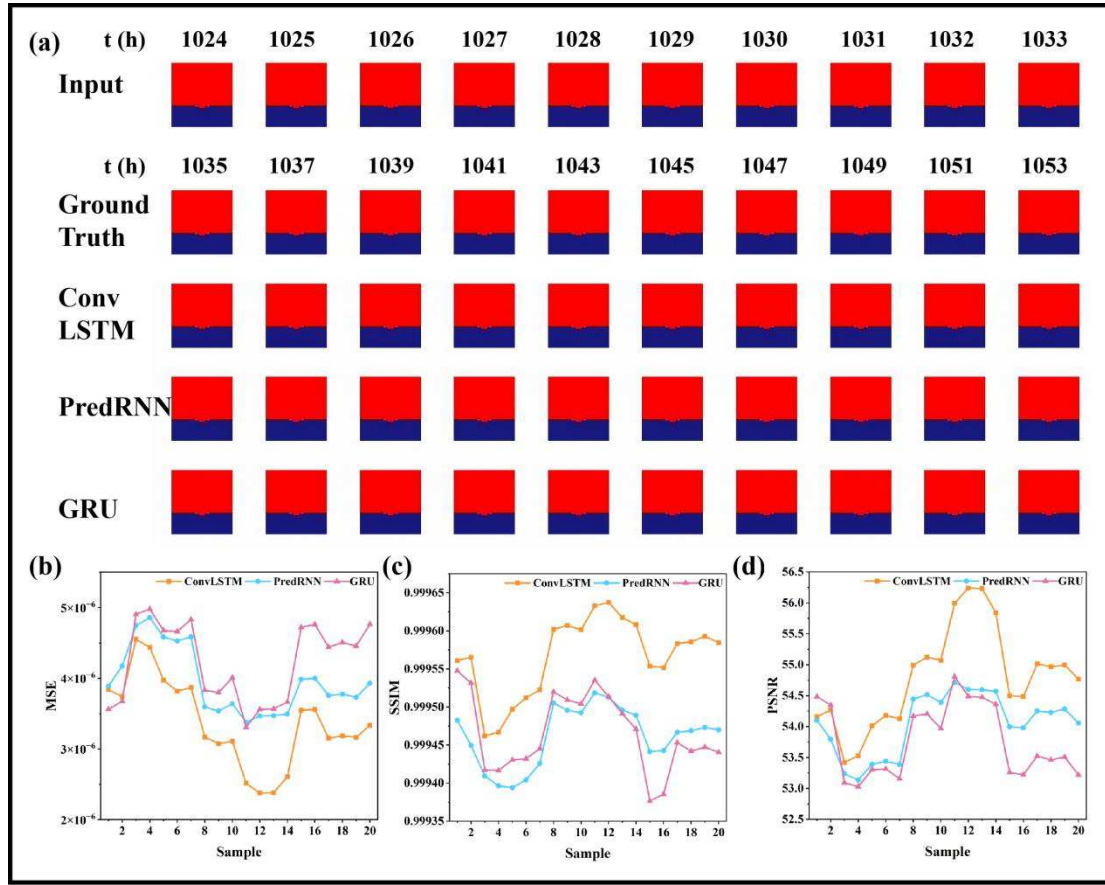


Figure 7. (a) Qualitative comparison of GRU, PredRNN and ConvLSTM predictions for corrosion images of a test sample ($\text{Cr}_2\text{N}/\text{Ni}_3\text{N}$). Single frame evaluation metrics (b) *MSE*, (c) *SSIM*, (d) *PSNR* curve ($\text{Cr}_2\text{N}/\text{Ni}_3\text{N}$) for GRU, PredRNN and ConvLSTM model.

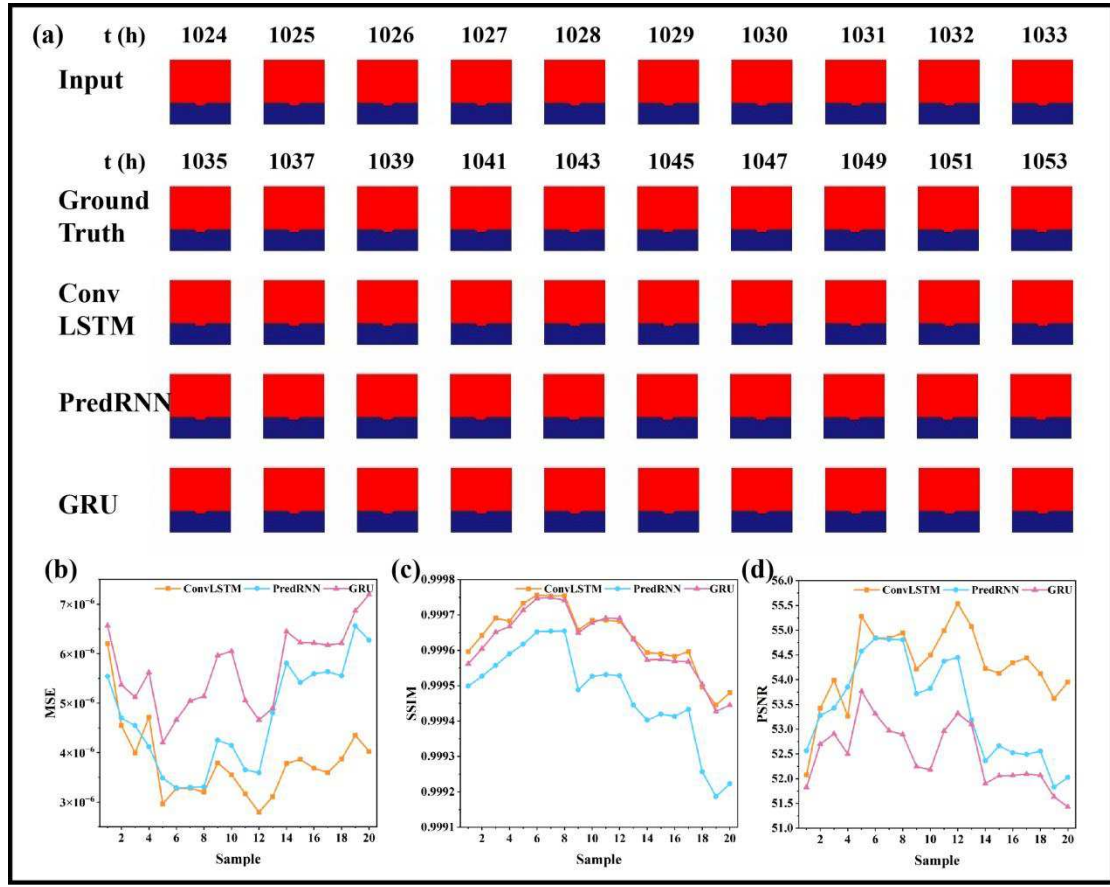


Figure 8. (a) Qualitative comparison of GRU, PredRNN and ConvLSTM predictions for corrosion images of a test sample (Epoxy). Single frame evaluation metrics (b) MSE , (c) $SSIM$, (d) $PSNR$ curve (Epoxy) for GRU, PredRNN and ConvLSTM model.

4. Conclusion

This study proposed a corrosion prediction framework fusing FEM and deep learning for the protective assessment of copper alloy relics. First, the corrosion evolution of four coating systems—WPU@ZIF-8, WPU@Ti₃C₂X, Cr₂N/Ni₃N, and Epoxy—within 1200 h was simulated via FEM, based on which a spatiotemporal corrosion dataset containing 4800 images was constructed. On this foundation, the prediction performance of three models—GRU, ConvLSTM, and PredRNN—was trained and compared. The results show that all three can effectively capture the spatiotemporal dynamics of the corrosion interface, but ConvLSTM and PredRNN are significantly superior to GRU, which relies solely on temporal modeling, in

morphology reconstruction accuracy. Among them, ConvLSTM, leveraging the strong capability of its convolutional structure to extract localized spatial features, achieved the best performance in prediction accuracy, structural fidelity, and long-term prediction stability. Comprehensively, the proposed FEM-deep learning fusion strategy provides an efficient alternative pathway for the rapid assessment of relic corrosion states and offers a quantitative theoretical basis for the rational screening of protective systems and preventive maintenance decision-making. Future work will focus on the model's generalization capability under non-uniform corrosion and sudden environmental perturbations.

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References

1. Angelini, Emma Paola Maria Virginia, Simone Corbellini, Franco Ferraris, Sabrina Grassini, Yangwu Mao, and Marco Parvis. 2010. *An Impedance Spectroscopy System for the In-Situ Assessment of the Conservation State of Archaeological Bronzes*. Curran. https://iris.polito.it/handle/11583/2397455?__cf_chl_f_tk=XPjojobpms5vK06_cpLgpDsslrN6cUINjYQM3QFAJhU-1782808710-1.0.1.1-Us3x3unhHv6aMu0SP_WicDcRQtf6aalq1dU.3ep5p5Y.
2. Brum, Douglas, Luan Teylo, Fabricio Polifke Da Silva, et al. 2026. "Assessing the Environmental Costs of Multi-Scale Recurrent Neural Networks for Sustainable Extreme Rainfall Nowcasting." *Scientific Reports* 16 (1): 12846. <https://doi.org/10.1038/s41598-026-43029-2>.
3. Cao, Haoyu, Zhipeng Liang, Yiyong Wang, and Hui Jin. 2024. "Study of Initial Corrosion and Protection Behavior of Bronze from the Western Zhou Dynasty Assisted by BTA." *Corrosion Science* 239 (October): 112419. <https://doi.org/10.1016/j.corsci.2024.112419>.
4. Chen, Kunlong, Thilo Rehren, Jianjun Mei, and Congcang Zhao. 2009. "Special Alloys from Remote Frontiers of the Shang Kingdom: Scientific Study of the Hanzhong Bronzes from Southwest Shaanxi, China." *Journal of Archaeological Science* 36 (10):

- 2108–18. <https://doi.org/10.1016/j.jas.2009.04.016>.
5. Chen, Xue-Xiang, Shi-Yong Yu, Anne P. Underhill, and Hui Fang. 2018. “Radiocarbon Dating and Stable Carbon Isotopic Analyses of Neolithic and Bronze Age Staple Crops in the Lower Yellow River Area and Their Paleodietary Implications.” *Geoarchaeology* 33 (3): 307–13. <https://doi.org/10.1002/gea.21659>.
 6. Cofini, Elena, Elena Bernardi, Luca Ciacchi, et al. 2025. “The Role of Particulate Matter in Bronze Corrosion: A Novel Method for Assessment and Prediction.” *Science of The Total Environment* 968 (March): 178845. <https://doi.org/10.1016/j.scitotenv.2025.178845>.
 7. Gollé-Leidreiter, Marcel, Julian Schneider, Konstantin Kapfer, et al. n.d. “Corrosion Prediction Approach Combining FEM-Simulations and AI-Modules for Complex Automotive Geometries.” *Materials and Corrosion* n/a (n/a). <https://doi.org/10.1002/maco.70127>.
 8. Horé, Alain, and Djemel Ziou. 2010. “Image Quality Metrics: PSNR vs. SSIM.” *2010 20th International Conference on Pattern Recognition*, August, 2366–69. <https://doi.org/10.1109/ICPR.2010.579>.
 9. Hosseini, Seyed Hossein, Harri Koivusalo, Jussi Nikander, and Henrikki Tenkanen. 2025. *A Scoping Review of Spatiotemporal ConvLSTM Applications for Predicting Water Balance Components*. December 10. <https://eartharxiv.org/repository/view/11101/>.
 10. Jain, Aakanksha. 2026. “Erosion-Corrosion Wear of Cr₂N/Ni₃N Multi-Layer Coating Deposited on Nickel Aluminium Bronze (NAB) Using the DC Magnetron Sputtering System.” *Ceramics International*.
 11. Katona, Ryan Michael, Aditya Venkatraman, Matthew Roop, Philip James Noell, David Montes de Oca Zapiain, and Rebecca Filardo Schaller. 2024. “(Invited) Finite Element Modeling of Atmospheric Corrosion: Boundary Conditions, Model Fidelities, and Computational Advances with Machine Learning.” *ECS Meeting Abstracts* MA2024-02 (17): 1699. <https://doi.org/10.1149/MA2024-02171699mtgabs>.
 12. Kwon, Heehong, and Namchul Cho. 2024. “In-Situ Non Destructive Investigation of Contemporary Outdoor Bronze Sculptures.” *Heritage Science* 12 (1): 167. <https://doi.org/10.1186/s40494-024-01280-8>.
 13. Li, Bingbing, Qixing Xia, and Wenqiang Dong. 2025. “Comparative Study of the Corrosive Behaviors of Rust Layers on Bronze Ware in Different Corrosive Environments.” *Materials* 18 (6): 1359. <https://doi.org/10.3390/ma18061359>.
 14. Liu, Chao, and Robert G. Kelly. 2019. “A Review of the Application of Finite Element Method (FEM) to Localized Corrosion Modeling.” *Corrosion* 75 (11): 1285–99. <https://doi.org/10.5006/3282>.
 15. Liu, Wei. 2025. “Advances in Understanding Bronze Disease Corrosion Mechanisms and Humidity Threshold Studies.” *Journal of Beijing University of Chemical Technology* 52 (5): 23–31. <https://doi.org/10.13543/j.bhxbzr.2025.05.003>.
 16. Qi, Xinke, Aobin Liu, Yuanyuan Li, Lanxue Dang, Jinglai Zhang, and Li Wang. 2025. “Deep Learning and Finite Element Simulation of Spatiotemporal Multiscale

- Fusion: Real Time Prediction of Magnesium Alloys Corrosion Covered with MAO Coatings.” *Materials Today Communications* 44 (March): 111915. <https://doi.org/10.1016/j.mtcomm.2025.111915>.
17. Roqui, David, Adèle Cormier, nistor Grozavu, and Ann Bourges. 2025. “A Multimodal Approach to Heritage Preservation in the Context of Climate Change.” arXiv:2510.14136. Preprint, arXiv, October 15. <https://doi.org/10.48550/arXiv.2510.14136>.
 18. Rosenberg, Danny, and Rivka Chasan. 2018. “The Characteristics and Significance of Prestige Goods during the Early Bronze Age Period of the Southern Levant: The Particular Case of the Four-Handled Basalt Vessels Phenomenon.” *Quaternary International*, “Humans and Quaternary Environments in the Levant” in Honour of Professor Mina Weinstein-Evron, vol. 464 (January): 241–59. <https://doi.org/10.1016/j.quaint.2017.04.021>.
 19. Sahlmann, Lisa, Nourhan Abdelrahman, Mats Meeusen, et al. 2026. “Surrogate Modelling of Corrosion Inhibition Finite Element Simulations Using Machine Learning.” *Npj Materials Degradation* 10 (1): 38. <https://doi.org/10.1038/s41529-026-00760-5>.
 20. Sandu, I., N. Ursulescu, I. G. Sandu, O. Bounegru, I. C. A. Sandu, and A. Alexandru. 2008. “Pedological Stratification Effect of Corrosion and Contamination Products on Byzantine Bronze Artefacts.” *Corrosion Engineering, Science and Technology* 43 (3): 256–66. <https://doi.org/10.1179/174327807X234688>.
 21. Shi, Xingjian, Zhourong Chen, Hao Wang, Dit-Yan Yeung, Wai-kin Wong, and Wang-chun Woo. 2015. “Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting.” arXiv:1506.04214. Preprint, arXiv, September 19. <https://doi.org/10.48550/arXiv.1506.04214>.
 22. Sun, Hongshuo, Li Song, and Zhiwu Yu. 2024. “Bridge Damage Localization and Quantification Using Deep Learning and FEM Static Simulation.” *Mechanical Systems and Signal Processing* 211 (April): 111177. <https://doi.org/10.1016/j.ymssp.2024.111177>.
 23. Wang, Huai, Yong Fan, Limei Tian, Jie Zhao, and Luquan Ren. 2020. “Colorimetric/FLuorescent Dual Channel Sensitive Coating for Early Detection of Copper Alloy Corrosion.” *Materials Letters*.
 24. Wang, Xiuyuan, Herong Zhou, Jialiang Song, et al. 2024. “Mechanism of Corrosion Behavior between Pb-Rich Phase and Cu-Rich Structure of High Sn–Pb Bronze Alloy in Neutral Salt Spray Environment.” *Journal of Materials Research and Technology* 29 (March): 881–96. <https://doi.org/10.1016/j.jmrt.2024.01.068>.
 25. Wang, Yunbo, Haixu Wu, Jianjin Zhang, et al. 2023. “PredRNN: A Recurrent Neural Network for Spatiotemporal Predictive Learning.” *IEEE Transactions on Pattern Analysis and Machine Intelligence* 45 (2): 2208–25. <https://doi.org/10.1109/TPAMI.2022.3165153>.
 26. Wu, Jinxian, Wugan Luo, and Mingyi Zou. 2026. “Semi-Quantitative Evaluation of the Stability of Chloride-Induced Patina on Bronze under Humidity Cycling Using

- Non-Contact Multimodal Techniques.” *Corrosion Science* 265 (June): 113796.
<https://doi.org/10.1016/j.corsci.2026.113796>.
27. Wu, Wenling, Xuan Zhang, Yinghao Chen, et al. 2024. “Multifunctional Organic-Inorganic Hybrid Coating for Enhanced Bronze Corrosion Protection.” *Journal of Cultural Heritage* 69 (September): 113–25.
<https://doi.org/10.1016/j.culher.2024.08.003>.
28. Wu, Wenling, Xuan Zhang, Anding Shao, et al. 2025. *Organic–Inorganic Composite Strategy for Fluorinated Waterborne Polyurethane (WPU)@ZIF-8/Ti3C2Tx Coatings to Achieve Superior Anticorrosion Properties for Bronze Protection*.
29. Yang, Yanpeng, Xiaojuan Cao, Yang Li, et al. 2020. “Spontaneous Symmetry-Breaking in the Corrosion Transformation of Ancient Bronzes.” *Minerals* 10 (8): 656.
<https://doi.org/10.3390/min10080656>.
30. Zhang, Lingling, Chao Yang, and Yingzhi Guo. 2024. “Corrosion and Protection of Chinese Bronze Relics: A Review.” *Coatings* 14 (9): 1196.
<https://doi.org/10.3390/coatings14091196>.
31. Zhu, Litao, Wen Dai, Jiru Huang, and Zicong Luo. 2024. “A Comparative Analysis of Deep Learning Models for Accurate Spatio-Temporal Soil Moisture Prediction.” *Geocarto International* 40 (1): 2441382.
<https://doi.org/10.1080/10106049.2024.2441382>.
32. Zhu, Qinzhe, Tingting Pan, Liangbo Lv, Nan Feng, and Xi Yang. 2026. “An Image Segmentation-Based Quantitative Method for Assessing Corrosion Risk Levels in Bronze Artifacts.” *Npj Heritage Science*, ahead of print, June 20.
<https://doi.org/10.1038/s40494-026-02732-z>.