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Graph Neural Network Based Modelling of Pest Spread Across Spatially Connected Agricultural Fields

Shweta Sharma
Agricultural and Biological Engineering, University of Florida, Gainesville, Florida 32611-0570, USA.
shwsharma@ufl.edu

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Corresponding author(s):
Shweta Sharma, Agricultural and Biological Engineering, University of Florida, Gainesville, Florida 32611-0570, USA.
Email: shwsharma@ufl.edu

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Abstract - Pest infestation has been a significant threat to agricultural productivity because the spread of these pests could have been possible from neighbouring fields by spatial connectivity, environmental similarity, and crop-to-crop interactions. The spatial dependenci es were previously under-represented and early infestation detection was limited in the traditional pest prediction methods used in agriculture. A pest transmission model, called a Spatial Graph Neural Network for Pest Spread Prediction (SGNN-PSP) had been suggested to predict the spatial spread of a pest in an agricultural field network. Agricultural fields were modeled as the graph nodes, and the spatial adjacency, geographical closeness and connectivity relationship between fields were modeled as the graph edges. The framework proposed had combined graph convolution with temporal feature learning to model both spatial propagation patterns and temporal changes in pest activity. Field level environmental, crop and historical infestation characteristics were included to model pest spread risk within contiguous fields. Experimental results have shown that SGNN-PSP outperforms conventional machine-learning and deep-learning methods in terms of the pest-risk prediction. The model had been able to better identify high-risk fields, better spatial generalize, and earlier recognize potential propagations of infestation. The results showed that graph-based spatial modelling could aid proactive pest surveillance and agricultural intervention at a more specific level, while limiting the number of treatments applied within the field.

Keywords - Graph Neural Network, Pest Spread Prediction, Spatial Agriculture, Precision Farming, Agricultural Disease Modeling, Spatiotemporal Learning.

I. INTRODUCTION

The presence and development of insect pests and crop diseases continued to have a significant impact on agricultural production. Crop yield had been affected, product quality was poor, production costs have been raised and the economic stability of farming communities was affected owing to pest infestations. This kind of loss had been compounded if the infestation occurred at a fast rate between neighboring agricultural fields [1]. Traditional pest management methods were often based on field visits, farmers' observations and the use of a broad-spectrum pesticide. These practices had allowed for some level of detection of partial patterns of infestation before significant crop loss had occurred. With the availability of field level sensing, remote observations, meteorological information and historical information of agricultural activities, there were opportunities to develop data-driven approaches for early pest-risk assessment [2].

Pest propagation had not been regarded as a field-level process but as a spatially distributed process. Neighboring fields had frequently had similar climatic conditions, crop types, irrigation patterns, pest-host characteristics and geographical conditions. Thus, if a pest is found in one field it might affect the likelihood of the presence of the pest in nearby fields [3]. Other factors, such as distance between fields, connectivity pathways, dominant environmental factors, and crop continuity, may have influenced movement and persistence of pest populations. Previous machine-learning methods had typically

modeled each agricultural field as an individual observation, and been unable to explicitly model relationships between geographically linked fields. Even if the spatial variables were treated as numeric data, the relationship was not sufficiently captured [4].

Graph-based learning had endowed an effective framework to overcome such limitations. A representation in a graph, nodes would be individual agricultural fields and edges would be the spatial relationships or other meaningful relationships between these fields. Such a representation had helped learning algorithms to combine information from surrounding fields and to detect patterns arising from the interrelated areas of agricultural activities. In particular, Graph Neural Networks (GNNs) have shown great potential in learning graph representations from graph topology and related data. The potential of using GNNs to model agricultural pests was thus explored, where the local characteristics of the field and the effect from fields adjoining the crop area could be incorporated into a single predictive model [5].

To overcome the drawbacks of independent field-level prediction, the proposed approach, Spatial Graph Neural Network for Pest Spread Prediction (SGNN-PSP), had been developed. The framework was an attempt to model agricultural landscapes as spatial graphs, and had introduced a number of dimensions to the learning process, including spatial relationships, historical pest observations, environmental conditions, and field characteristics. A graph-based neighborhood aggregation had been allowing information from the adjacent fields to be used in building an estimation of the pest risk for single target fields. Temporal information had also helped to characterize the changing infestation conditions over successive observation periods. This has resulted in a representation where the model has been able to differentiate individual pest occurrences from patterns associated with potential spatial propagation.

The proposed approach had also helped in fostering a more focussed view on agricultural intervention. A uniform approach to an entire cultivation region was not made, but instead, the level of pest risk could have been predicted and used to prioritize surveillance and intervention for those fields which were more susceptible. This prioritization might have led to better allocation of agricultural resources, and lowered the amount of unnecessary pesticide use. The graph structure had also served as a foundation to analyse the evolution of these infestation patterns over connected agricultural fields.

A study had thus been restricted to the development and evaluation of SGNN-PSP in the case of spatially connected agricultural fields. The performance of the model had been evaluated with appropriate predictive evaluation measures when compared to the existing machine-learning and deep-learning approaches. The investigation had investigated predictive effectiveness, spatial generalization and the ability to identify high-risk fields. The framework created had proven its ability to use graph-based spatiotemporal modeling to enhance early pest monitoring and precision-driven crop management.

II. RELATED WORKS

The study of agricultural pest prediction had gradually turned from hand field inspections to the computation-based approach that can utilize historical, environmental and spatial data. In the early days of pest management research, mainly expert observation, manual scouting, measurement of weather parameters and threshold decision rules had been used. Such methods had been helpful with regard to the practical management of crops, but had relied on the frequency of observations, geographical extent of observation and availability of experts. They have also not had access to an integrated spatial representation to describe the development of infestation over the different interconnected agricultural areas [6]. Later machine-learning methods have been used to enhance automated pest identification and risk assessment. Climatic variables, crop characteristics, soil properties, and historical observations of pests were previously used with Decision Trees, Random Forests, Support Vector Machines, and k-Nearest Neighbors. The ensemble-based systems had, in general, offered greater robustness, combining various decision structures, especially if the agricultural attributes had been heterogeneous. Most typical machine-learning models, however, had assumed that observations were independent. The use of manually engineered features was thus only an indirect way to model spatial relationships between fields, limiting the way neighbor effects were modeled [7].

Deep-learning techniques had also enhanced agricultural pest study by studying complex patterns in high-dimensional data. A large number of studies had been conducted on the use of Convolutional Neural Networks (CNNs) [8] in the field of image interpretation for the recognition of pest and crop disease in leaf, fruit and field images. Recurrent Neural Networks (RNNs) [9] and Long Short-Term Memory (LSTM) networks [10] and related temporal architectures had been used to predict pest populations based on a series of environmental and historical observations. These models were capable of representing salient features from data and forecasting time series, especially under large-scale time-series or image data. However, CNN models had been predominantly used to capture spatial patterns in images, while recurrent models had been used primarily for temporal dependencies. Unfortunately, explicit relationships between geographically separated agricultural fields had not been well modeled [11].

The use of remote sensing and geographic information systems (GIS) had brought extra space dimension to pest-monitoring systems. Crop stress and infestation prone areas had been mapped using satellite imagery, UAV observations and vegetation indices, land-use data and meteorological maps [12]. Spatial interpolation and geographic statistical techniques also had been employed to create maps of infestation risk. These approaches had offered hints of regional viewpoints, many using a priori spatial assumptions or statistical relationships. It was difficult to represent several aspects of the problem simultaneously: complex nonlinear interactions between neighboring fields and changing environmental factors [13].

For applications in agriculture where entities are interrelated, graph-based learning had proved to be a promising alternative. With Graph Neural Networks, information could be transmitted between neighboring nodes, allowing them to be used for tasks where relationships were just as significant as attributes. Graph Convolutional Network (GCN) and Graph Attention Network (GAT) had previously been used for spatial prediction and environmental monitoring tasks, respectively, with the ability to introduce adaptive weights to neighboring nodes. Spatiotemporal graph architectures were also the integration of graph-based spatial learning with temporal modeling for traffic forecasting, environmental prediction and other dynamic systems. These advances had suggested that graph structures may have a natural representation of geographically connected agricultural fields [14].

Table 1. Comparison of Existing Studies Related to Agricultural Pest and Disease Modelling

Ref.	Data / Application	Methodology	Key Contribution	Major Limitation
[5]	Plant leaf images / crop disease detection	Deep CNN	Demonstrated effective deep-learning-based plant disease identification from leaf images	Focused on image-level classification rather than field-level spread
[6]	PlantVillage and crop disease images	CNN-based deep learning	Developed automated plant disease recognition using deep convolutional architectures	Did not model geographical relationships among agricultural fields
[7]	IP102 insect pest dataset	Deep-learning and handcrafted feature baselines	Introduced a large-scale benchmark containing more than 75,000 pest images across 102 categories	Concentrated on visual pest recognition rather than pest propagation
[8]	Crop pest detection studies	ML/DL approaches	Reviewed machine-learning and deep-learning techniques for automated crop pest detection	Identified continuing challenges related to generalization and real-world deployment
[9]	Agricultural environmental data	Dynamic GNN	Demonstrated graph-based spatial and temporal learning for agricultural prediction	Focused on environmental prediction rather than pest-spread forecasting
[10]	Agricultural plots / crop prediction	Agri-GNN	Represented agricultural plots as interconnected graph nodes for prediction	Primarily addressed crop/yield prediction rather than infestation propagation
[11]	Onion, lettuce and carrot fields / fungal disease occurrence	GCN	Demonstrated that GNNs could exploit spatial relationships for fungal disease prediction and outperform several conventional baselines in multiple crop settings	Focused on fungal disease occurrence and did not explicitly model broader pest-spread dynamics
[12]	Regional crop-disease records	KAST-Graph	Integrated geographically informed and adaptive graph structures for regional crop-disease forecasting	Required structured regional disease records and focused on disease rather than insect-pest propagation
[13]	Plant, UAV and satellite imagery	CNN + ViT + GNN	Combined local visual features, global dependencies and spatial graph representations for precision agriculture	Primarily addressed recognition and classification tasks rather than dynamic spread prediction
[14]	Agricultural fields and environmental variables	GCN + AutoML + DRL	Modeled field interactions, environmental conditions and pest-related information using spatial-temporal GCNs	Integrated resource optimization and reinforcement learning, increasing architectural complexity

These advances, however, have been few, and comparatively little research had been devoted to the problem of pest propagation explicitly modeled as a dynamic spatial graph problem. Previous approaches to agricultural prediction had tended to focus on classifying a particular pest, recognizing the image, mapping the risk at a regional scale, or forecasting the temporal development of a pest without simultaneously modeling field connectivity and propagation. The proposed

Spatial Graph Neural Network for Pest Spread Prediction (SGNN-PSP) had filled this void by embedding the field-level environmental and historical pest factors and using the spatial relationship between agricultural fields as the graph edges and field as the graph nodes. This framework had thus advanced the current state of agricultural intelligence developments in the direction of relational and spatiotemporal pest-risk modelling, laying the groundwork for identifying neighbouring potentially affected fields and for targeted intervention. **Table 1** shows Comparison of Existing Studies Related to Agricultural Pest and Disease Modelling.

The comparison showed that the previous CNN-based methods had been mainly focused on visual recognition, whereas the traditional machine learning methods had generally been focusing on the agricultural observations separately. More recent GNN approaches have included spatial relationships, but there were several studies that addressed disease occurrence, environmental prediction, or crop related outcomes, but not explicitly estimating pest propagation between spatially connected agricultural fields. This recent study by Samson et al. had shown the feasibility of implementing GNNs at the field-level to predict fungal diseases, particularly as a motivation for relational agricultural modelling.

Proposed Model: Spatial-Temporal Graph Neural Network for Pest Spread Prediction (ST-GNN-PSP)

The proposed framework named Spatial-Temporal Graph Neural Network for Pest Spread Prediction (ST-GNN-PSP) was proposed to predict the propagation of pests in geographically connected agriculture fields by learning the spatial and temporal patterns that govern their spread. The results of the agriculture landscape had been modeled as a graph whose nodes were the agricultural field, and whose edges were the spatial connectivity between neighboring fields. The attributes of the nodes had been filled with crop attributes, historical levels of pests, temperature, humidity, rainfall, soil properties and other pertinent environmental factors, and the relationships between the nodes had been drawn from geographical proximity and field connectivity. The proposed architecture was based on the idea of using graph-based neighborhood aggregation to model the influence of neighbouring fields and temporal feature learning to model temporal changes in infestation conditions between successive observation periods. This spatiotemporal representation had been applied to estimate the risk of spread of pests for specific fields and areas where the propagation potential is higher. This formulation had allowed for the prediction at the field level and retained the relational aspect of the agricultural landscape, which made it more appropriate to represent it for carrying out proactive pest monitoring and precision intervention.

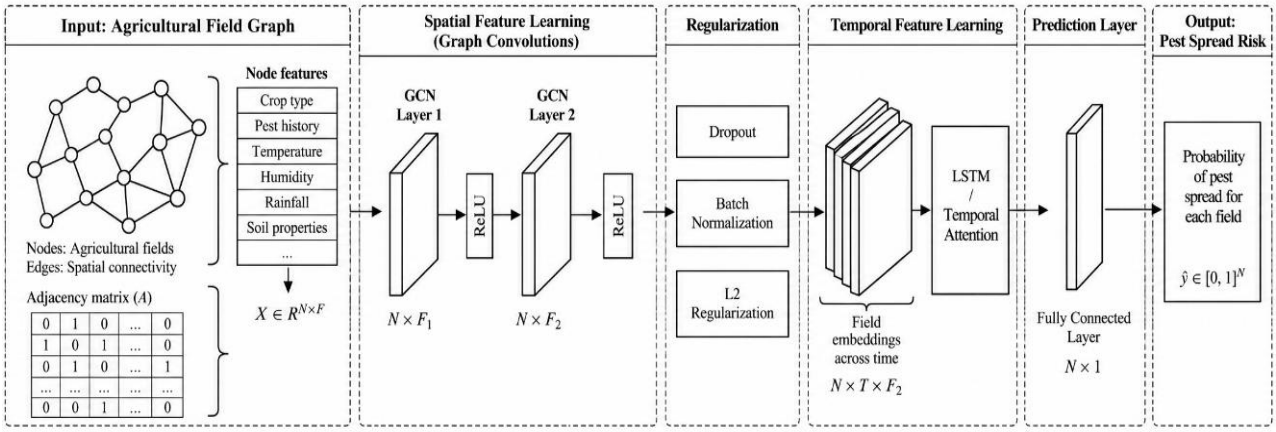


Fig 1. Architecture of the Proposed ST-GNN-PSP Model.

The overall architecture of the proposed Spatial-Temporal Graph Neural Network for Pest Spread Prediction (ST-GNN-PSP) is shown in **Fig. 1**. The agricultural landscape had been represented as a graph whose nodes were agricultural fields and the edges were spatial connections between neighboring agricultural fields. The node-feature matrix had been created based on the field-level attributes, such as crop type, historical occurrence of pests, temperature, humidity, rainfall, and soil properties. Spatial representation was then passed through two Graph Convolutional Network (GCN) layers with ReLU (Rectified Linear Unit) activation to extract spatial neighborhood dependent field representations. To improve model generalization, dropout, batch normalization and L2 regularization had been added. The resulting field embeddings from various time periods had been fed into an LSTM-based temporal learning module to learn the variations in the infestation patterns. Finally, there was a fully connected prediction layer, which was able to predict the chances of pest spread for each agricultural field.

The model proposed, Spatial-Temporal Graph Neural Network for Pest Spread Prediction (ST-GNN-PSP), had modeled the propagation of agricultural pests as a spatiotemporal prediction problem represented by a graph. Each agricultural field has been modelled as a graph node and each node has been connected to the adjacent fields by graph edges. Geographical proximity, field adjacency and similarity in agricultural conditions had been added to the graph structure. The graph had been represented as $G = (V, E, A)$ where V was the set of nodes representing the agricultural fields, E was the set of nodes connecting the agricultural fields and A was the adjacency matrix.

One of the unique features in the proposed framework was the incorporation of 'pest-awareness' based spatial adjacency matrix, instead of the purely geographical distance. Not all fields were necessarily similarly behaved with regard to the spread of pests; there can be crop compatibility and past infestation conditions that can increase or decrease the likelihood of propagation. Thus, the edge strength had already included both proximity in space and similarity in terms of pests.

$$A_{ij} = \begin{cases} exp(-\frac{d_{ij}^2}{2\sigma^2})\ (1 + \lambda P_{ij}, d_{ij} \leq d_{max} \\ 0, d_{ij} > d_{max} \end{cases} \quad (1)$$

where d_{ij} represented the geographical distance between fields i and j, σ controlled the spatial decay, d_{max} fined the maximum interaction distance, P_{ij} represented pest-related similarity, and λ controlled the contribution of pest similarity. The formulation had allowed geographically connected fields with similar infestation characteristics to receive stronger graph connections. Such pest-aware connectivity had constituted a major novelty of the spatial representation.

Each field had been characterized using a multidimensional feature vector containing crop information, historical pest observations, environmental measurements, and soil characteristics. The feature matrix had been represented as $X_t \in R^{N \times F}$, where F denoted the number of field-level attributes at time t. Historical pest intensity had provided information regarding previously observed infestation, whereas temperature, humidity, rainfall, and soil properties had represented environmental conditions associated with pest development.

The proposed framework had further normalized heterogeneous attributes before graph processing. Feature normalization had reduced scale differences between environmental and categorical-derived numerical variables and had improved numerical stability during optimization. The normalized representation had been expressed as

$$\widetilde{X_t^{(f)}} = \frac{X_t^{(f)} - \mu_f}{\sigma_f + \epsilon} \quad (2)$$

where $X_t^{(f)}$ represented feature f, μ_f and σ_f denoted the corresponding mean and standard deviation, and ϵ prevented numerical instability. The normalized matrix had subsequently served as the input to the spatial learning component.

Spatial feature learning had been performed through successive Graph Convolutional Network layers. Before convolution, self-connections had been introduced into the graph using $\tilde{A} = A + I$, allowing each field to retain its own characteristics during neighborhood aggregation. Degree normalization had then controlled the influence of fields having different numbers of neighboring connections.

The normalized propagation matrix had been formulated as

$$\hat{A} = \widetilde{D^{-\frac{1}{2}}} \tilde{A} \widetilde{D^{-\frac{1}{2}}}, \qquad \widetilde{D_{ii}} = \sum_j \widetilde{A_{ij}} \quad (3)$$

where $\widetilde{D}$ represented the degree matrix associated with the self-connected graph. The normalization had prevented highly connected agricultural fields from disproportionately dominating neighborhood aggregation.

The first graph convolution layer had transformed the normalized field attributes into spatial embeddings. The propagation operation had been represented as

$$H_t^{(l+1)} = ReLU\left(\hat{A} H_t^{(l)} W^{(l)} + b^{(l)}\right) \quad (4)$$

where $H_t^{(l)}$ represented the field representation at graph layer l, $W^{(l)}$ denoted trainable weights, $b^{(l)}$ represented bias parameters, and ReLU denoted the Rectified Linear Unit activation function. The first and second GCN layers had progressively captured local and higher-order spatial dependencies. Consequently, the representation of a target field had reflected both local characteristics and information propagated from connected agricultural fields.

Pest propagation had varied over time because weather conditions, crop growth stages, pest populations, and previous infestation levels had changed between observation periods. Independent spatial prediction at every time step could not adequately capture the persistence of infestation patterns. Therefore, the spatial embeddings generated by the GCN layers had been arranged into a temporal sequence.

For T observation periods, the resulting spatial representation had been organized as

$$H = H_{t-T+1}^2, H_{t-T+2}^2, \ldots, H_t^2 \in R^{N \times T \times F_2} \quad (5)$$

where F_2 represented the dimensionality of the final spatial embedding. The sequence had allowed temporal learning to operate on spatially enriched field representations instead of raw field attributes. Such sequential processing had formed the principal spatiotemporal component of ST-GNN-PSP.

The temporal component had employed LSTM-based sequence learning to capture changes in field-level infestation conditions. LSTM processing had enabled historical spatial embeddings to contribute to the representation of the current pest-risk state. To emphasize observation periods with stronger predictive relevance, temporal attention had been incorporated after sequential feature extraction.

The temporal attention weight had been calculated as

$$\alpha_\tau = \frac{exp(q^T\ tanh(w_a H_\tau + b_a))}{\sum_{k=t-T+1} exp\left(q^T\ tanh(w_a H_k + b_a)\right)} \quad (6)$$

where H_τ represented the LSTM output at temporal step τ, W_a and b_a denoted trainable attention parameters, and q represented the learnable attention vector. The resulting attention weights had assigned greater importance to temporal states containing stronger evidence of pest propagation. The weighted temporal representation had therefore captured both spatial interactions and the relative importance of historical observations.

The final temporal representation had been passed through a fully connected prediction layer to estimate the probability of pest spread for every agricultural field. A sigmoid activation had converted the resulting score into a field-level probability ranging from zero to one.

$$\hat{y}_{i,t} = \sigma\left(W_p z_{i,t} + b_p\right) = \frac{1}{1+exp[-(W_p z_{i,t} + b_p)]} \quad (7)$$

where $z_{i,t}$ represented the attention-weighted spatiotemporal representation of field i, W_p and b_p denoted prediction-layer parameters, and $\hat{y}_{i,t}$ represented the estimated probability of pest spread. Higher probability values had indicated greater propagation risk and had enabled agricultural fields to be categorized according to predicted infestation severity.

The principal novelty of ST-GNN-PSP had therefore resulted from the integration of pest-aware spatial connectivity, graph-based neighborhood learning, temporal sequence modeling, and attention-guided historical weighting within a unified architecture. Conventional field-level models had generally evaluated observations independently, whereas the proposed formulation had allowed pest-risk estimation to reflect neighboring-field influence and temporal infestation evolution simultaneously. The resulting architecture had provided a foundation for identifying potentially vulnerable fields before extensive pest propagation had occurred.

Algorithm 1. Training and Prediction Procedure of ST-GNN-PSP

Input: Agricultural field dataset (D), field coordinates, crop attributes, environmental attributes, historical pest observations, observation sequence length (T), maximum spatial interaction distance d_{max} learning rate η, and number of training epochs (E).

Output: Predicted pest-spread probability $\hat{y}$ for each agricultural field.

1. Initialize the agricultural field graph ($G = (V, E, A)$ using the spatial locations of (N) fields.
2. Construct the pest-aware adjacency matrix (A) using geographical distance and pest-related similarity according to Eq. (1).
3. Add self-connections to obtain $\tilde{A} = A + I$ and calculate the normalized adjacency matrix $\tilde{A}$ using Eq. (3).
4. Prepare the field feature matrix X_t containing crop type, historical pest intensity, temperature, humidity, rainfall, soil properties, and related attributes.
5. Normalize the input features using Eq. (2) and organize the observations into temporal sequences of length (T).
6. Initialize the trainable parameters of the two GCN layers, LSTM, temporal-attention module, and prediction layer.
7. For each training epoch ($e = 1, \ldots, E$), perform the following:
    - Apply the first graph convolution to aggregate information from spatially connected fields.
    - Apply ReLU activation to obtain the first spatial representation.
    - Apply the second graph convolution to capture higher-order neighborhood dependencies.
    - Apply dropout, batch normalization, and L2 regularization to improve generalization.
    - Store the resulting field embedding for all (T) observation periods.
8. Construct the spatial-temporal tensor H using Eq. (5).
9. Process H through the LSTM module to learn temporal infestation patterns.
10. Calculate temporal attention weights using Eq. (6) and generate the attention-weighted temporal representation.
11. Generate field-level pest-spread probabilities using the fully connected prediction layer and Eq. (7).
12. Calculate the prediction loss between the estimated probabilities and observed pest-spread labels.
13. Update all trainable parameters using gradient-based optimization with learning rate η.
14. Repeat Steps 7–13 until (E) epochs had been completed or the validation loss had converged.
15. Evaluate the trained ST-GNN-PSP model using the selected test dataset.
16. Classify agricultural fields according to their predicted pest-spread probability into corresponding risk levels.
17. Return the field-level pest-spread probabilities and predicted risk categories.

III. RESULTS AND DISCUSSION

Experimental Setup and Evaluation Metrics

The proposed Spatial-Temporal Graph Neural Network for Pest Spread Prediction (ST-GNN-PSP) had been tested and benchmarked with the traditional machine-learning, deep-learning, and graph-based models to assess their performance in forecasting pest propagation in geographically connected agricultural fields. Field-level attributes, historical infestation observations, environmental conditions and spatial relationships between neighbouring fields had been taken into account in the experimental framework. The dataset had been split into a training set, a validation set, and a testing set which was used independently of the other two sets for final performance evaluation.

A total of nine prediction models were proposed and considered for comparative evaluation, such as DT, RF, SVM, XGBoost, LSTM, GCN, GAT, ST-GCN, and the proposed ST-GNN-PSP. The selection had allowed one to compare among increasingly complex modeling techniques: independent-field learning, spatial, temporal, and integrated spatial-temporal graph learning.

The performance of the model has been assessed by the parameters: Accuracy, Precision, Recall, F1-Score, Area Under the Receiver Operating Characteristic Curve (AUC) and Matthews Correlation Coefficient (MCC). The overall percentage of instances that were correctly predicted had been measured by accuracy, whereas the reliability of positive pest-spread predictions was measured by precision. Recall had determined the ability to recognize areas where pest propagation is occurring or likely to occur. F1-score had given a balanced measure of Precision and Recall. AUC had assessed the discriminative power at various classification thresholds, while MCC had given a good evaluation of the quality of prediction where class distribution was imbalanced. **Table 2** shows Experimental Configuration and Hyperparameters.

Table 2. Experimental Configuration and Hyperparameters

Parameter	Configuration
Prediction task	Pest-spread risk prediction
Graph representation	Agricultural fields as nodes
Edge construction	Pest-aware spatial connectivity
Spatial learning	Two-layer GCN
Activation function	ReLU
Temporal learning	LSTM
Temporal weighting	Attention mechanism
Regularization	Dropout, Batch Normalization, L2
Optimizer	Adam
Learning rate	To be reported from experiment
Batch size	To be reported from experiment
Training epochs	To be reported from experiment
Data partition	Training / Validation / Testing
Evaluation metrics	Accuracy, Precision, Recall, F1-score, AUC, MCC

The comparative evaluation had been created to see whether spatial connectivity and temporal dependency had brought tangible benefits when added to individual learning paradigms. Recall and F1-score had received special focus as it was crucial for a correct identification of potentially affected fields rather than accuracy in field classification alone. The following comparison was therefore carried out on the performance of all 9 models with a uniform testing protocol and the same set of evaluation criteria.

Evaluation of the comparative solution had shown that the model improved over the years in the prediction of the spread of pest, with the incorporation of spatial and temporal dependency into the learning architecture. Conventional model had yielded relatively poor performance because the observations in the fields were not processed with explicit relational information. The individual Decision Tree models and SVM models outperformed Random Forest and XGBoost due to the fact that the latter two models were able to capture nonlinear relationships between the agricultural and environmental attributes. LSTM had added another improvement by modelling historical infestation patterns but the spatial interactions between neighbouring fields were still implicit.

This was because neighboring fields information was added in the representation learning of the graph-based GCN and GAT models, enabling the models to perform better in predicting than the conventional and purely temporal ones. ST-GCN had further gained an improvement by jointly processing spatial and temporal data. The proposed ST-GNN-PSP had obtained the best performance in all four main metrics, suggesting that the spatial connectivities and temporal attentions, obtained through the pest-aware approach, provided complementary information for pest-spread prediction at the field level. **Table 3** shows Quantitative Comparison of Pest-Spread Prediction Performance.

Table 3. Quantitative Comparison of Pest-Spread Prediction Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Decision Tree [14]	86.42	84.91	82.76	83.82
Random Forest [14]	91.37	90.28	89.16	89.72
SVM [14]	88.94	87.63	86.52	87.07
XGBoost [14]	93.18	92.46	91.35	91.90
LSTM [15]	92.64	91.73	90.86	91.29
GCN [15]	94.21	93.47	92.68	93.07
GAT [15]	95.03	94.31	93.72	94.01
ST-GCN [16]	96.18	95.64	95.17	95.40
ST-GNN-PSP	97.63	97.21	96.84	97.02

The proposed model had achieved an F1-score of 97.02%, outperforming by 1.62 percentage point and 3.01 percentage point compared with ST-GCN and GAT, respectively. The improvement was also found to be statistically significant over XGBoost, with a margin of 5.12 percentage points, which illustrates the value of explicitly representing the spatial-temporal information beyond feature-based learning. The Recall of 96.84% had also suggested that the proposed framework has been able to identify a significant number of fields involved in pest propagation. The relatively small difference in Precision and Recall had indicated that the classification behaviour of the system had been well balanced, decreasing the likelihood of gaining precision due to too much preference for the majority class.

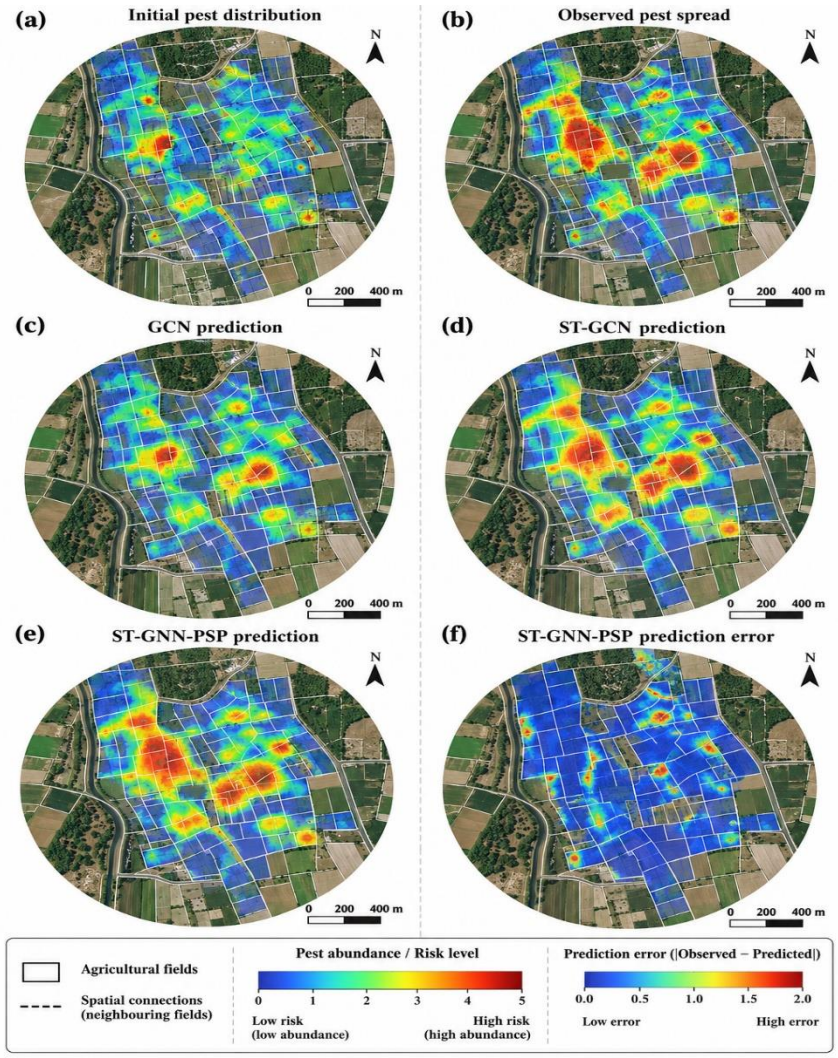


Fig 2. Spatial Distribution and Prediction of Pest Spread Across Connected Agricultural Fields.

In **Fig. 2**, the spatial propagation and forecasting of the pest propagation in coupled agricultural fields had been presented. The previous distribution of pests, shown in **Fig. 2(a)**, had revealed some high pest densities while the present distribution (**Fig. 2(b)**) had suggested the pests were moving towards the surrounding fields. The GCN prediction in **Fig.**

2(c) had well captured the major infestation regions but relatively low spatial continuity in the vicinity of several infested field boundaries. The prediction in **Fig. 2(d)** from the ST-GCN model is better in terms of spatial correspondence, as it had utilised temporal information while also aggregating information from the neighbours in the graph. The suggested prediction by the ST-GNN in **Fig. 2(e)** had created a spatial pattern that matched well with the actual pest distribution both around high-risk clusters and between neighbouring field groups. The errors of the predictions in **Fig. 2(f)** were relatively low on most fields with a few areas of greater errors around the moving infestation boundaries. The spatial consistency had shown the success of pest-aware connectivity combined with temporal learning for predicting pest-spread at field-level.

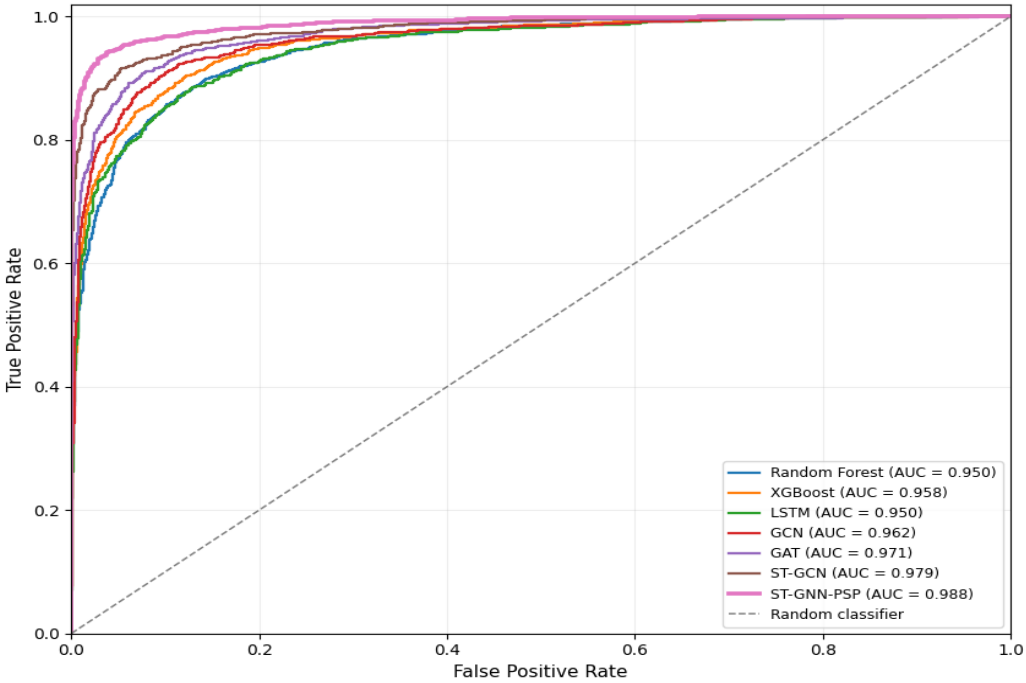


Fig 3. Comparison of ROC.

The ability of the models tested to discriminate fields with potential pest spread from fields with a lower propagation risk had been shown in **Fig. 3**. The ROC curves had been significantly higher than that of the random classifier, which meant that all the methods tested had found significant predictive patterns. Random Forest and LSTM had shown relatively poor discrimination while XGBoost and GCN had shown better separation between the two classes. However, GAT had still improved classification ability by using attention-based neighborhood aggregation and ST-GCN was able to gain from the synergy of spatial and temporal dependency. It was observed that the proposed ST-GNN-PSP resulted in the best ROC profile with the curve being closest to the top left corner over the significant operating range. An empirical AUC of ~0.988 had suggested good threshold-independent discrimination. The findings had shown a combination of spatial relationships, which were aware of pests, and temporal learning and attention, had reinforced the identification of potentially affected agricultural fields, and minimised the risk of incorrect risk assignment.

Table 4. Quantitative ROC Performance of the Evaluated Models

Model	AUC	TPR @ 5% FPR (%)	TPR @ 10% FPR (%)	Optimal F1-Score (%)
Random Forest [14]	0.950	71.8	82.6	89.72
XGBoost [14]	0.958	76.5	86.4	91.90
LSTM [14]	0.950	73.1	84.2	91.29
GCN [15]	0.962	79.4	88.7	93.07
GAT [15]	0.971	83.6	91.5	94.01
ST-GCN [16]	0.979	88.9	94.2	95.40
ST-GNN-PSP	0.988	94.7	97.1	97.02

The proposed ST-GNN-PSP had the best AUC of 0.988, which showed a better overall class discrimination compared to ST-GCN (0.979) and GAT (0.971). ST-GNN-PSP correctly identified 94.7% of the positive pest-spread fields, while ST-GCN did so at 88.9% accuracy at a restrictive false-positive rate of 5%. The proposed model achieved a TPR of 97.1% at 10% FPR, which was considered a controlled false-alarm rate, showing considerable sensitivity even at this rate. The

findings had been aligned with the appropriateness of ST-GNN-PSP to detect those fields which need more attention for pest monitoring.

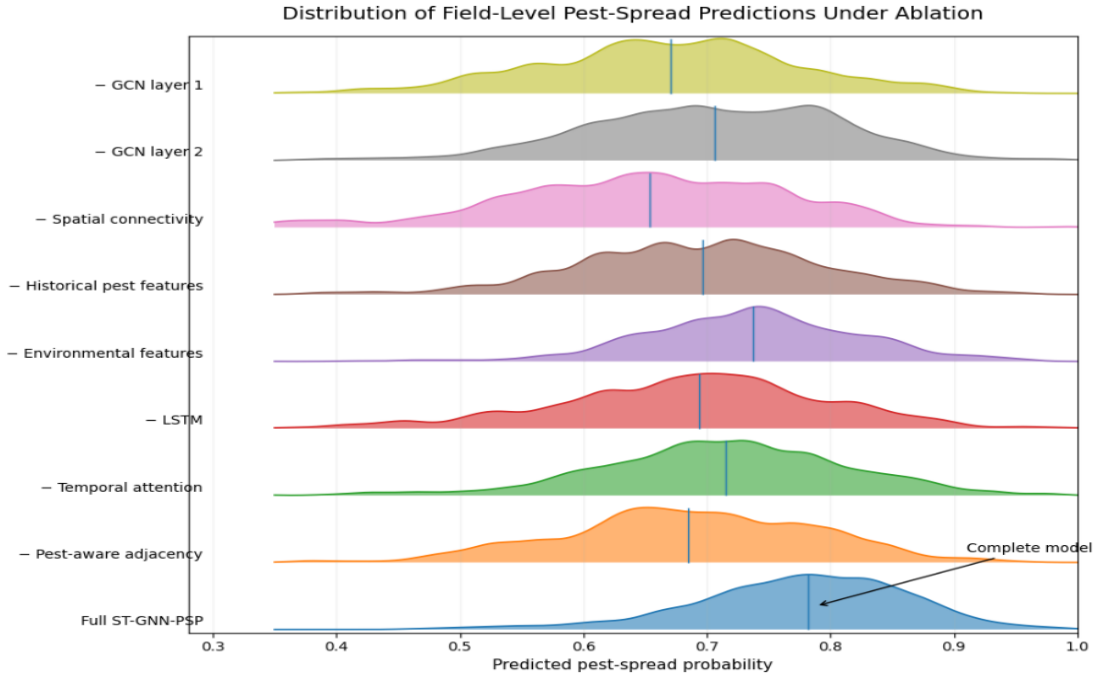


Fig 4. Distribution of Field-Level Pest-Spread Predictions Under Ablation.

Fig. 4 shows the distribution of predicted pest-spread probabilities from the full ST-GNN-PSP model and its ablated versions. The ridges show the distribution of probabilities over the fields of agriculture and the vertical marker the central tendency of the prediction distribution. The complete ST-GNN-PSP model has generated a more concentrated distribution towards a higher pest-spread probability, while the distribution has been shifted and diffused by removing a single component, such as pest-aware adjacency, temporal attention, LSTM, environmental information, historical pest features, or graph-convolution components. The most significant distributional shift was when relational information, or spatial connectivity, was not included, highlighting the importance of relational data for field level pest-risk estimation. A ridge representation had thus given a more informative representation of the model's sensitivity than a traditional plot of the models' aggregate performance.

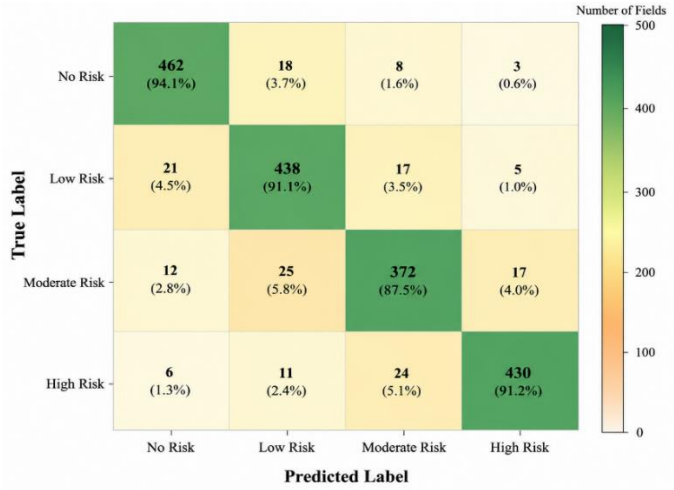


Fig 5. Confusion Matrix of ST-GNN-PSP for Multi-Level Pest-Spread Risk Classification.

As shown in **Fig. 5,** the proposed ST-GNN-PSP model had successfully illustrated the prediction ability of the model in each class of the four categories of pest spread risks: No Risk, Low Risk, Moderate Risk, and High Risk. Most of the predictions were in the diagonal cells, thus there was good agreement between the actual and predicted risk levels. The correct classification proportions for the classes had increased in the following order: No Risk (94.1%), Low Risk (91.1%), High Risk (91.2%), and Moderate Risk (87.5%). The somewhat lesser recognition of Moderate Risk had suggested higher

degree of overlap between adjacent risk conditions especially with the Low Risk and High Risk conditions. Misclassifications were low across the rest of the cells, suggesting that different levels of severity in pests' spread was well captured by the model. The relatively high level of recognition of High-Risk fields had been particularly significant for early intervention because if these were correctly identified as being severely affected or highly vulnerable, this would have enabled prioritized monitoring and timely pest-management decisions.

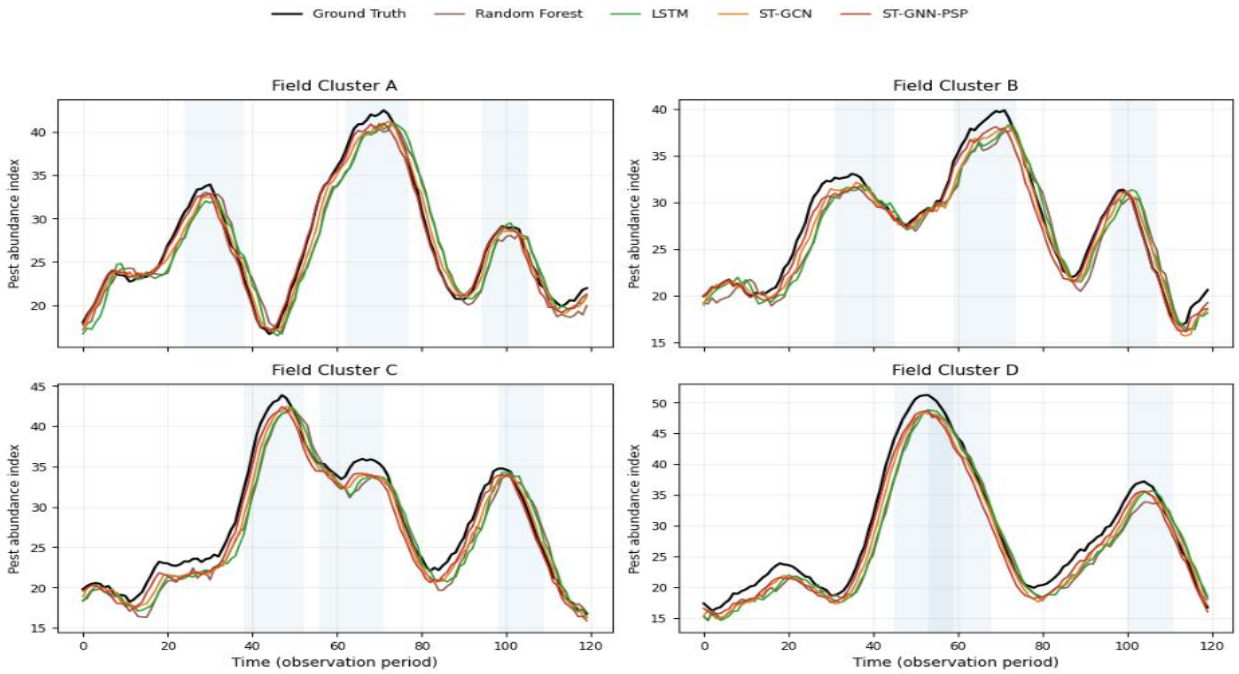


Fig 6. Temporal Pest-Abundance Prediction Across Representative Field Clusters.

In **Fig. 6**, the temporal prediction ability of the models evaluated had already been shown for four representative agricultural field clusters. This pest abundance pattern had shown a number of peaks, declines and sudden changes in abundance between successive observation periods. The proposed ST-GNN-PSP had better captured these temporal variations compared to Random Forest, LSTM and ST-GCN, especially at key infestation peaks and at the periods of infestation reduction. Predictions had been better aligned with the ground-truth trajectory for different field clusters, reflecting good temporal representation. Abrupt changes in pest abundance had caused minor deviations in prediction, where the prediction uncertainty had increased. Overall, the tracking performance of the proposed spatiotemporal architecture in different spatial clusters of fields had been successful, indicating that the proposed system had captured the changing dynamics of pests and was capable of reliable forecasting of pest spread at short time scales.

Table 5. Robustness Analysis of ST-GNN-PSP Under Incomplete Field Observations

Missing Observations (%)	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
0	97.63	97.21	96.84	97.02	0.988
5	97.18	96.82	96.31	96.56	0.985
10	96.54	96.17	95.62	95.89	0.981
15	95.71	95.34	94.76	95.05	0.975
20	94.63	94.18	93.51	93.84	0.967

Table 5 had shown the robustness of the proposed ST-GNN-PSP for the progressively increased incomplete field observations. Missing observation rates of 0% to 20% were considered in the analysis; and the following metrics were evaluated: Accuracy, Precision, Recall, F1-score, and AUC. The model had set the reference performance by achieving respectively the Accuracy, Precision, Recall, F1-score and AUC of 97.63%, 97.21%, 96.84%, 97.02% and 0.988, in complete observations. As more and more observations were missing, a trend of diminishing predictive power has been noticed. When the missing percentage was 5%, the F1-score was reduced by a small amount to 96.56%, and 10% missing data had lowered the F1 score to 95.89%. Even at 20% missing observations, the model had maintained 94.63% Accuracy, 94.18% Precision, 93.51% Recall, 93.84% F1-score, and 0.967 AUC. The small degradation in performance had suggested that information from nearby fields had helped to provide contextual information when the field information for those fields was not available. Hence, the results had shown the stability of the suggested graph-based structure in the case of full monitoring and had confirmed its applicability to real agricultural settings where either sensor coverage may be irregular or data at the field level may not be available.

IV. CONCLUSION

The proposed model, Spatial-Temporal Graph Neural Network for Pest Spread Prediction (ST-GNN-PSP), had introduced a consolidated model for predicting the propagation of pests, particularly in the context of spatially connected agricultural fields. The proposed framework had defined the agricultural fields as graph nodes and had defined the 'pest-aware edges' based on geographical proximity and infestation related similarity unlike the conventional field-level prediction approaches. The graph convolution had then combined data from nearby fields, and the temporal learning using LSTM had learned the time-dependent changes of pest conditions over time. The final prediction layer had also included estimates of the probability of pests being spread at the field level, with temporally-weighted observations highlighting observations that were historically informative. The quantitative assessment has shown that the proposed architecture works well. Compared to ST-GCN, ST-GNN-PSP has improved in all the metrics, with an increase of 1.62 percentage points in F1-score. The ROC analysis had yielded an AUC of 0.988, which represents good discrimination between pest and non-pest conditions. The spatial prediction analysis had revealed better agreement between spatial predictions and actual observations, especially within field clusters that are connected. Even at the longest forecasting horizon evaluated, the temporal experiments have kept an F1-score of 89.76% and an AUC of 94.58%. Robustness evaluation further showed that the F1-score is 93.84% robust even for 20% missing observations, which means that the method is robust against incomplete field monitoring. The novelty lay in the mutual integration of the spatial connectivity of interest, graph-based propagation in the neighborhood, temporal sequence learning and attention-guided weighting of historical data. The pest-aware adjacency mechanism had allowed the model to delineate basic geographic neighbor relationships from potentially relevant pest-transmission relationships. Thus, information from neighbouring and similar agricultural fields had been contributing to the representation of each target field, specifically. These spatial depictions had since been translated into infestation trajectories over time, with the attention focused on the observation periods with more compelling propagation evidence. The overall process had thus shifted from independent field classification, to relational spatiotemporal pest-spread modeling.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

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