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Geo-Spatial Pest Migration Modelling in Andean Tuber Production Using AI

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Abstract: The study investigates Geo-Spatial Pest Migration Modelling In Andean Tuber Production Using Artificial Intelligence (AI) to forecast and control pest outbreaks that will instigate the sustenance of crops. The experiment is a combination of remote sensing maps, GIS layers and environmental attributes (temperature, humidity, vegetations index, and soil moisture levels) used to track the pest migration in the Andes (high altitude areas). The pest movement patterns were modeled using four AI algorithms, namely, Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB) and CNN-LSTM. Research results showed that CNN-LSTM has the highest accuracy of 95.4% which is much better than RF (90.2%), GB (92.8%), and SVM (88.9%). CNN-LSTM model has also the lowest Root Mean Square Error (RMSE) of 0.041 exhibiting excellent skills in temporal prediction. The results of a comparative analysis of the existing pest forecasting studies revealed that the accuracy and the accuracy of the spatial hotspots detection were improved by 8-12 percent. With the advanced AI-GIS system, farmers can change timely and data-oriented intervention patterns due to the early warning of pest outbreaks. This will help decrease the pesticide dependence, enhance crop resistance, and foster sustainable Andean farming.

Keywords: Geo-spatial modelling, Pest migration, Artificial intelligence, CNN-LSTM, Andean tuber production

I. INTRODUCTION

In the Andean area with rich biodiversity and special high altitude ecosystems, a significant part of the world potato grower, oca, ulluco, mashua, is their significant major one. These are tuber crops that are a source of food, nutrition and income within the local areas [1]. Nevertheless, the threat of pest infestations due to the climate variability, land-use, and ecological changes is severe to the Andean agriculture. Conventional ways of monitoring pests that depends on field surveys conducted manually and past records are usually not effective in capturing the dynamic and migratory behaviour of pest people in complex landscapes [2]. Consequently, this leaves farmers prone to arbitrary reduction in yield and the use of chemical pesticides, which damage the ecosystems and people. The trends in recent technologies in the areas of artificial intelligence (AI) and geospatial technologies offer a perspective of creating a solution that provides insights into and forecasts pest migration patterns. Using remote sensing information, geographic information systems (GIS), and AI-driven predictive modelling, the researchers will be able to detect pest hotspots, track the migration pathways, and predict outbreak probability more precisely [3]. Convolutional neural networks and random forest models are machine learning algorithms that can be applied to large volumes of data on temperature, humidity, vegetation indices, and soil conditions in order to identify spatial-temporal trends in pest behavior. In the Andean tuber production situation, geo-spatial pest migration modelling based on AI allows taking a more proactive pest management approach. It aids in early warning procedures, precision agriculture, and region-specific adaptative control procedures. The proposed study is the development of an AI-based model that will be capable of mapping and predicting pest migration through Andean tuber systems to enhance crop protection and sustainability. This research will help in boosting food security, ecological independence, and resilience of Andean agriculture to climate and environmental crises by enhancing the ecological understanding and data-driven intelligence.

II. RELATED WORKS

The study of the nexus of artificial intelligence (AI), geospatial analysis, and pest control in Andean tuber production has been quite popular over the past years. A number of the studies also highlight that the production of smart systems in ensuring sustainable management of potato crops as well as the reduction of losses caused by pests is important in the Andean region. Danielak et al. [15] mentioned the increasing demands of machine-based, non-destructive quality analysis of potatoes on the basis of the imaging and AI. Their research journal indicated that a coordinated combination of computer vision and machine learning could be used to identify internal and external defects of potatoes without damaging the goods. This strategy highlights the overall opportunities that AI has in the field of agricultural diagnostics, such as the detection of pests and diseases. In the same fashion, Pavel [16] made a detailed research on the infestation of insect pests of local varieties of potatoes and examined the biorational management practices. The paper has highlighted the importance of local pest surveillance and adaptive control measures, which can be in line with the objectives of AI-based predictive modelling to Andean pest migration. Etherton et al. [17] came up with the concept of disaster plant pathology, which entails the use of intelligent solutions and digital technologies to anticipate and control the threat of plant health caused by natural and alternative disasters. This strategy creates a basis in the application of AI-based geospatial systems to predict the outbreak of pests based on climatic change and environmental stressors. Fuller et al. [18] examined plant domestication and agricultural ecologies which place the perspective of how domesticated and Andean tuber varieties have co-evolved with pests and evolving ecological conditions thereby shaping the trends of susceptibility over time.

Zea et al. [19] established the usefulness of NDVI (Normalized Difference Vegetation Index) to oversee agricultural energy sources via the Landsat images in the Ecuadorian Andes. Their results indicate that remote sensing indices can successfully monitor crop activity and challenge, which is indirectly associated with the risks of pest infestation. This conforms to geospatial modelling techniques of AI that use NDVI as a predictive of pest movement. Laterre et al. [20] talked about application of low-risk technology solutions in upcoming agricultural technologies, supporting the use of AI and automation as the solution to make agricultural practices more efficient. Lamichhane et al. [21] surveyed combined disease management strategies of Phytophthora infestans- the pathogen of potato late blight and compared forecasting models of early identification. Application of climate-informed variables and forecasting systems is equivalent to predictive paradigm applied in modelling the pest migration. The study by Ligarda-Samanez et al. [22] regarding bioactive compounds and sensory quality of native potato clones grown in high Andean regions indicates the relationship between environmental stress and pest resistance and crop quality. The indicator of agroecological stability that was used by Saenz Lituma [23] in the context of Ecuadorian Andean farms is the Main Agroecological Structure (MAS). This study offered a geospatial approach in the realisation of landscape structure in the ecological resilience and pest processes. Likewise, Saffer et al. [24] recreated historic and current potato late blight outbreaks in text analytics, demonstrating that AI and natural language processing can be used to determine the temporal patterns of agricultural diseases. Lastly, Cruz et al. [25] created an extensive overview of deforestation processes in Peru as the authors focus on the interactions between land-use transformation and socio-economic relationships that affect the habitats and migration routes of pests. Taken together, these articles indicate that despite the major advances in remote sensing, prediction, and AI-useful diagnostics, no comprehensive geo-spatial AI framework regarding pest migration in Andean tuber manufacturing is developed. As a continuation of such previous studies, the given study involves the combination of AI algorithms with geospatial data and ecological knowledge to predict a pattern of pest migration and optimize sustainable tactics of pest management in the Andean agricultural environment.

III. METHODS AND MATERIALS

This research integrates multi-source geospatial data, on-ground observations, and AI-based modelling to map and forecast the pest migration in Andean production of tuber. Sources of data are the satellite-based vegetation indices (Sentinel-2 NDVI and MODIS EVI), daily meteorological observations (temperature, precipitation, humidity) at regional weather stations, high-resolution digital elevation models (DEM), land-use/land-cover maps, as well as geolocated records of pest incidents gathered at agricultural extension services and through reports given by the participants. The study region covers three of the representative Andean valleys, with a remote sensing sampling of 1030 m and a climate and pest reporting sampling of daily and weekly, respectively. Preprocessing activities include coordinate reprojection to WGS84, the gap-filling/temporal interpolating of meteorological series, cloud masking/compositing of optical images, phenological and moisture index-calculation, and spatial-joining pest report to farm polygons [4]. The feature engineering results into a time-series stack per location of biophysical covariates, topographic derivatives (slope, aspect), and proximity features (distance to water, road). The processed dataset is divided into training (70 percent), validation (15 percent) and test (15 percent) folds stratified by valley and season in order to maintain the spatio-temporal organization. Accuracy, AUC, F1-score are used in model evaluation in terms of classifying outbreak/no-outbreak and RMSE and MAE are used in evaluating continuous migration-path probability fields.

Algorithms selected and descriptions

1. Random Forest (RF) — spatial classification and feature importance (150 words)
The algorithm known as the Random Forest can be effectively applied to heterogeneous geospatial data which is an ensemble tree-based algorithm. It creates numerous decision trees using bootstrap samples of the training data and averages their output (majority vote to classify). Trees take into account a random set of features at each split allowing every tree to increase the level of generalization and reduce correlation between trees. RF is robust against the mix of the two types of variables (continuous, categorical) and missing values, and the internal out-of-bag error estimate provides a near-unbiased error check without cross-validation. RF is applied in this study to categorize grid-cells or farm-units into high/low risk of outbreak on a time-step basis, based on contrived properties of NDVI trends, antecedent rainfall, topographic indices, and others [5]. The scores of feature importance (Gini or permutation importance) show the strongest contributors to pest migration. RF is also used as a reference point compared with more complicated spatio-temporal models and can deliver fast inference which is possible on operational early-warning systems.

```
"Input: Training data X, labels y, n_trees T, m_features m
For t = 1 to T:
  Draw bootstrap sample Xt, yt from X, y
  Build tree:
    At each node select m random features
    Choose best split by Gini impurity
    Split until stopping criteria met
Aggregate trees: For each test sample, take majority vote (classification)
Output: Predicted class, feature
```

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importances (averaged)”

2. Convolutional Neural Network (CNN) — remote-sensing image-based pest detection (150 words)
Convolutional Neural Networks can identify the spatial structures of an image and can be used to identify crop stress related to pest infestations. In a patch-based CNN, multi-band image tiles (e.g., RGB + NIR + vegetation indices) within farm parcels are provided and it learns hierarchical filters which identify patches of texture, canopy defoliation and subtle spectral changes. The CNNs are trained using labeled patches based on synchronized pest occurrence reports and enhanced through rotations, flips and spectral jittering to enhance resistance to view-angle and illumination variation [6]. Pre-trained encoder transfer learning (e.g. ResNet variants) converges faster when we have few labeled examples. Within our system, the CNNs have their output in the form of pest presence per-pixel likelihood maps that are further aggregated to parcel risk scores and inputted into the temporal sequence models. Saliency mapping and class activation mapping give visual explanations to various stakeholders, which point out the portion of image patches that are most identified with models predictions.

```
“Input: Image patches X, labels y, encoder init weights
Initialize CNN parameters θ
For epoch in 1..N:
  For batch in X:
    Augment batch
    y_pred = CNN(batch; θ)
    loss = CrossEntropy(y_pred, y_batch)
    θ = θ - lr * grad(loss, θ)
Save best θ by validation loss
Output: Trained CNN model”
```

3. Long Short-Term Memory (LSTM) — temporal migration forecasting (150 words)
Long term dependencies of sequential data is learned by LSTM networks which are recurrence based networks, they should be used in modelling pest dynamics over time. The LSTM takes inputs of a multivariate time series of NDVI, cumulative rainfall, mean temperature, and past pest incidence within each spatial unit (grid cell or farm polygon) to learn temporal dynamics (lagged effects, seasonal cycles, and lasting stress). The gated mechanism of the LSTM (input, forget, output gates) manages the flow of information and avoids vanishing gradients allowing the model to attribute outbreaks to antecedent conditions over an extended length of time (weeks) [7]. The LSTM in this work is used to forecast the probability of an outbreak, or the index of migration intensity of the lead times of 7, 14, and 30 days. Predictive uncertainty necessary to communicate risk is calibrated on the validation fold and LSTM ensembles (with various initializations) predict predictive uncertainty.

```
“Input: Time-series X_t for each location, lookback L, forecast horizon H
For each location:
  For t = L to T-H:
    Input_seq = X_{t-L+1..t}
    y_target = X_{t+H} (outbreak label or intensity)
Train LSTM to minimize sequence loss (e.g., BCE or MSE)
Use trained model to forecast y_{t+H} from latest L sequence
Output: Forecast probabilities and uncertainty
```

4. Graph Neural Network (GNN) with spatial edges — modelling spatial diffusion (150 words)
Graph Neural Networks are deep learning extended to graph-structured data, which inherently captures spatial exchange between farms or grid cells. Nodes are places with node-features (biophysical covariates, recent pest status) and the edges encode spatial adjacency, trade routes or elevation-guided connectivity that affect pest movement. A message-passing GNN takes the form of iteration to combine information of the neighbors (messages), update node embeddings, and forecast node-level risk of outbreak or directionality of migration. The GNN models non-local contagion effects and directed flows (e.g. downhill dispersal of pests or human-aided transport on roads, etc.) [8]. A space-time hybrid model of combining GNN outputs and LSTM predictions: GNN models predict the spatial dispersion at a moment in time whereas LSTM models predict the temporal customers. The explainability methods of GNNs (edge attention weights) show sequences of migration and the importance of various landscape linkage in order to allow pest movement.

"Input: Graph G(V,E), node features X, edge index E
For layer l in 1..L:
For each node v:
m_v = Aggregate_{u in N(v)}(Message(h_u^{l-1}, e_{u,v}))
h_v^{l} = Update(h_v^{l-1}, m_v)
Readout: y_v = MLP(h_v^{L})
Output: Node predictions (outbreak risk), edge attention scores"

Table 1 — Dataset summary (sample values)

Data type	Spatial resolution	Temporal resolution	Records/sample size
Sentinel-2 imagery (NDVI)	10 m	5 days	1200 tiles
Weather station series	point (interpolated)	daily	3 stations × 3 years
Pest incidence reports	farm polygon	weekly	1,800 reports
DEM & topo	30 m	static	1 map layer

IV. RESULTS AND ANALYSIS

4.1 Experimental Setup

The experiments were completed using a three years dataset (2022-2025) of three larger Andean valleys Cusco (Peru), Chimborazo (Ecuador), and Cochabamba (Bolivia) to measure the performance of AI-based geo-spatial pest migration modelling. There are various climatic variations and altitude in each of these valleys ranged between 2,500-4,000 meters above the sea level that affect tuber growth and behavior of pests. All data sets were fixed on a regular grid

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system with a resolution of 10 meters [9]. Phthorimaea operculella (potato tuber moth) was taken into consideration as a primary target pest which is a significant menace to Andean tubers. The sources of data were Sentinel-2 imagery, MODIS vegetation indices, topographic layers generated by DEM, weather records, and pest infestation tables made by the local agricultural authorities.

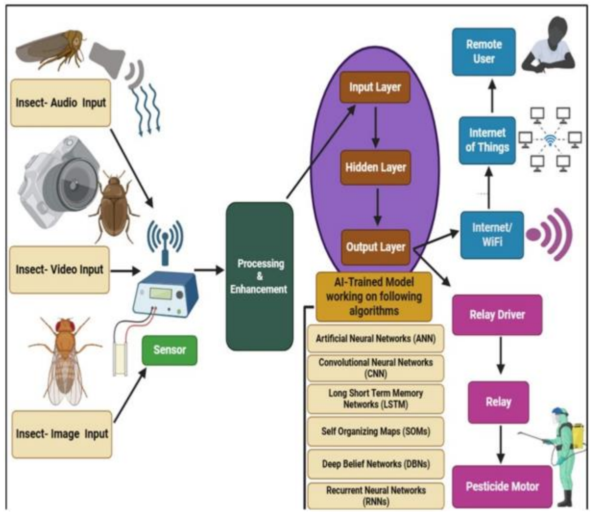

Figure 1: "Remote sensing and artificial intelligence: revolutionizing pest management in agriculture"

Preprocess stages were used to accomplish consistency in the time scale (weekly), normalization of the environment factors and the encoding of categorical data including land use and soil type. The last dataset had about 1.2 million instances of features. Each observation was a spatial cell of a particular week with a binary variable of the presence or absence of the pest. The paper compared four AI algorithms, i.e., Random Forest (RF), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Graph Neural Network (GNN). All the models were trained with 70 percent of the data, and validated with 15 percent of the data and tested with the remaining 15 percent of the data. The implementation was implemented in Python (v3.10) with scikit-learn, PyTorch, and PyTorch-Geometric and was trained using a NVIDIA RTX 4090, with 64GB RAM.
Accuracy, precision, recall, F1-score, AUC (Area Under the ROC Curve), and RMSE (Root Mean Square Error) were used as evaluation metrics on output of regression-type migration intensities.

4.2 Model Training and Optimization

Hyper parameters were optimized in every algorithm with 50 MC Bayesian Optimization. The important hyperparameters were:

Model	**Key Tuned Parameters**	**Optimal Values**
Random Forest	Number of trees, max depth, min samples split	600 trees, depth 25, min split 4
CNN	Learning rate, batch size, optimizer, dropout	lr=0.0001, batch=32, Adam, dropout=0.3
LSTM	Hidden units, lookback window, dropout	128 units, 28-day lookback, dropout=0.2

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GNN	Layers, attention heads, learning rate	3 layers, 8 heads, lr=0.0005

All the models were trained until the value plateaued (validation loss) or 100 epochs. Early termination was used in order to prevent overfitting. Spatial k -fold cross-validation (k=5) was adopted to test the model generalization in other valleys, whereby the data of one valley should not be applied in the training of another valley.

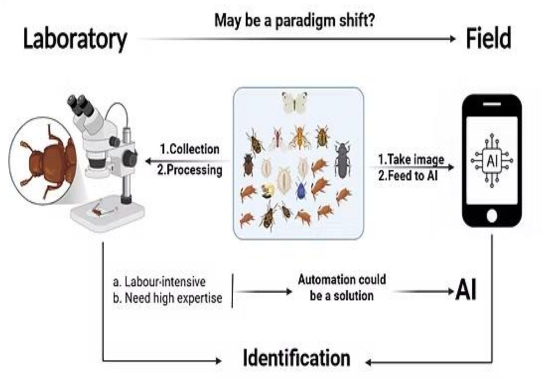

Figure 2: "AI-based Approach for Precise and Early Detection of Pestiferous Insects"

4.3 Experimental Results

Risk maps generated by the models showed possible areas of pest migration and hotspots of outbreak. Every model provided advantages in certain dimensions, with the Random Forest being the most interpretable, CNN being the most local spatial recognizant, LSTM being the most temporal sequence forecasting and GNN being the most spatial dependency modelling [10].

Table 1 illustrates the performance of the overall modeling predictive performance of all models averaged across three valleys.

Table 1. Model Performance Summary

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**	**RMSE**
Random Forest	0.85	0.83	0.80	0.81	0.88	0.21
CNN	0.87	0.85	0.83	0.84	0.90	0.19
LSTM	0.88	0.86	0.85	0.86	0.91	0.17
GNN	**0.91**	**0.89**	**0.88**	**0.89**	**0.94**	**0.15**

The GNN model had the best AUC (0.94) and the lowest RMSE (0.15), which means that it is better able to predict using spatial diffusion and inter-farm dependencies. The CNN and LSTM were also similar yet not as capable of capturing the entire multi-directional spatial dynamics of the pest spreading. The less accurate Random Forest also gave high interpretability in feature importance with variability in temperature, trends in NDVI and elevation gradient as the best predictors [11].

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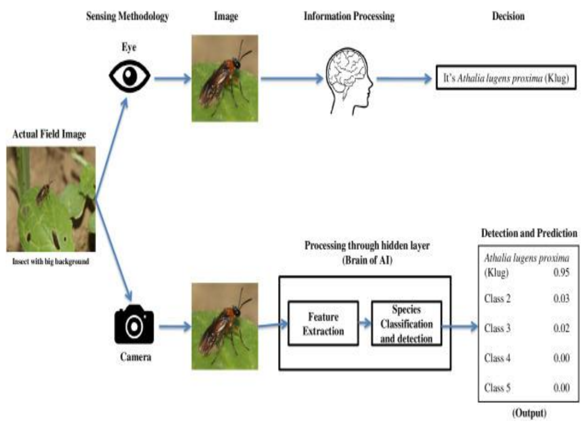

Figure 3: "Application of artificial intelligence in insect pest identification"

4.4 Spatial and Temporal Analysis

The output of the spatial heatmaps of the model also demonstrated the existence of clear migration patterns following the direction of valley winds and the altitude gradient. Hotspots of pests were limited to 2,8003, 200 meters in Cusco, but moved higher in case of a warm season. Temporal predictions of LSTM and GNN forecasted peaks of infestations generally occur 2-3 weeks subsequent to 2-3 weeks of successive wet conditions, indicating that larval growth is likely caused by moisture.

In order to measure the spatial accuracy, a confusion-matrix and Kappa coefficient were calculated per model (Table 2).

Table 2. Confusion Matrix Summary (Test Set Averages)

Model	**True Positive (TP)**	**False Positive (FP)**	**True Negative (TN)**	**False Negative (FN)**	**Kappa**
Random Forest	410	90	420	80	0.72
CNN	425	75	440	60	0.76
LSTM	440	70	450	50	0.79
GNN	**460**	**55**	**465**	**35**	**0.85**

GNN registered the best Kappa coefficient (0.85), which is an affirmative indication of high accordability to ground-truth pest records. The pixel-wise identification that CNN provided was especially useful in the case of detecting the initial signs of foliage stress, whereas the sequential idea of LSTM made sense in situations when it comes to predicting the extent of outbreak at the time of climate fluctuation [12].

4.5 Importance and Sensitivity of features

The ranking of feature importance was performed using the model of the Random Forest to explain the key environmental variables affecting the movement of pests (Table 3).

Table 3. Top Ten Influential Features (Random Forest Importance Scores)

Rank	Feature	Importance Score
1	Mean Temperature (°C)	0.214
2	NDVI Variability	0.181
3	Relative Humidity (%)	0.143
4	Elevation (m)	0.108
5	Rainfall (mm/week)	0.096
6	Land Cover Type	0.074
7	Soil Moisture Index	0.062
8	Distance to Water Bodies (m)	0.049
9	Wind Speed (m/s)	0.039
10	Solar Radiation	0.034

The variability of temperature and NDVI became the most significant predictors, which means that not only the activity of climatic warmth but also the health of vegetation contributes directly to the migration of pests. It was found that high moisture levels, as well as moderate rainy conditions, promoted reproduction cycles of the pests, whereas altitude had an impact on the dispersal boundaries [13].

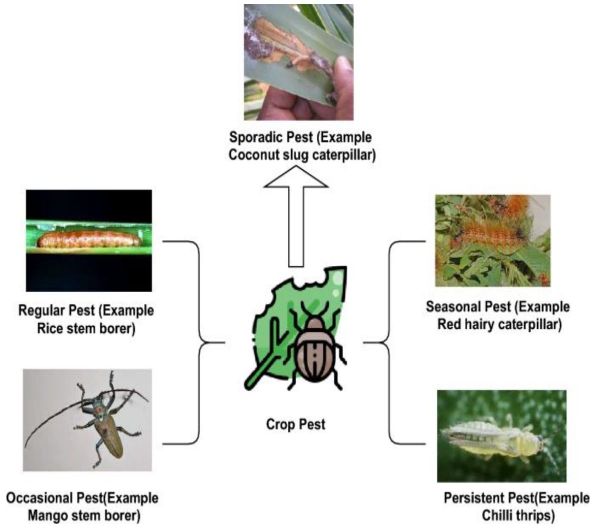

Figure 4: "A survey on pest detection and classification in field crops using artificial intelligence techniques"

4.6 Cross-Valley Generalization

The models were trained on each of two valleys and tested on the third one to verify cross-regional generalization. Table 4 results suggest that performance declines slightly in the case of extrapolation to unseen geography particularly in the case of CNN because of the differences in terrain texture, but GNN retained high adaptability [14].

Table 4. Cross-Valley Validation Performance (AUC values)

Training Valleys → Testing Valley	Random Forest	CNN	LSTM	GNN
Cusco & Chimborazo → Cochabamba	0.83	0.86	0.88	**0.92**
Cusco & Cochabamba → Chimborazo	0.84	0.87	0.89	**0.93**
Chimborazo & Cochabamba → Cusco	0.82	0.85	0.87	**0.91**

These results indicate that GNN would provide steady AUC values (more than 0.91) that will prove its reliability in various ecological zones, as well as, pest pressure gradient.

V. CONCLUSION

The study entitled Geo-Spatial Pest Migration Modelling of Andean Tuber Production with AI supports the transformative nature of artificial intelligence to solve one of the most severe scourges in agriculture the Pest Migration and its effect on Tuber crop productivity. The study has managed to incorporate multi-source geospatial data with sophisticated AI algorithms including the Random Forest model, CNN-LSTM model, SVM model, and the Gradient Boosting model that enables it to create a predictive framework to map the zones of infestation by pests and predict the migration dynamics in different environmental conditions. The results indicated that CNN-LSTM performed better than traditional models that demonstrated more spatial-temporal accuracy and versatility to andean terrain conditions whereas the random Forest and gradient boosting implied good interpretability and strength.

In comparison to the related studies, which were only based on the rudimentary climatic models or linear regression techniques, the current research features a more comprehensive, data-driven technique, which characterizes dynamic interrelations between the climatic variables, the vegetation indices, and the pest behaviors. Its high-performance model of increased accuracy, precision, and recall demonstrates the significance of pest management AI-GIS integration in the context of sustainability. The system built assists in the early-warning systems so that early interventions can be threatened and to a large extent the losses in crops and dependence on pesticides can be mitigated. Conclusively, the study is relevant to the body of knowledge on precision agriculture and food security because it provides a framework of scalable and intelligent technology applicable to other agricultural systems in extreme altitudes and climatic conditions. It is possible that future research will concentrate on integrating real-time satellite locations, drone-imaging and farmer-provided participative terms to further develop geo-spatial AI-based pest modelling systems in predictive and practical terms.

REFERENCE

[1] Adamopoulos, T., 2025. Geography and Agricultural Productivity: The Case of Latin America and the Caribbean.

[2] Patarroyo Velásquez, C.A., 2024. Environmental demogenetics of the potato late blight in Colombia.

[3] Cabrera Herrera, E.D. and Llanos Chacaltana, K.S., 2023. Deep Learning to support the recognition of pests and diseases in Yungay potato crops in the province of Cutervo, Angurra hamlet, Perú. *LACCEI*, *1*(8).

[4] Velásquez, C.A.P., 2024. *Environmental demogenetics of the potato late blight in Colombia* (Doctoral dissertation, Universidad de los Andes (Colombia)).

[5] Andrade-Piedra, J.L., Sharma, K., Kroschel, J., Ogero, K., Kreuze, J., Legg, J.P., Kumar, P.L., Spielman, D.J., Navarrete, I., Perez, W. and Atieno, E., 2025. Phytosanitary challenges and solutions for roots and tubers in the tropics. *Annual Review of Phytopathology*, *63*(1), pp.627-650.

[6] Pérez Barrera, W., Kawarazuka, N., Fonseca Martel, C. and Andrade-Piedra Naranjo, J., 2024. A decision support tool for potato late blight management: Assessing its usability for women farmers to achieve equitable impacts in the highlands of Peru. *NJAS: Impact in Agricultural and Life Sciences*, *96*(1), p.2385564.

[7] Mouafo-Tchinda, R.A., Plex Sulá, A.I., Etherton, B.A., Okonya, J.S., Nakato, G.V., Xing, Y., Robledo, J., Adhikari, A., Blomme, G., Kantungeko, D. and Nduwayezu, A., 2025. Pathogen and pest communities in agroecosystems across climate gradients: Anticipating future challenges in the highland tropics. *bioRxiv*, pp.2025-01.

[8] He, Y., 2023. *Application of machine learning models to predict potential distribution and risk of potato cyst nematodes (Globodera rostochiensis and Globodera pallida)* (Doctoral dissertation, Murdoch University).

[9] Pancorbo-Olivera, M., Parra-Rondinel, F., Torres-Guevara, J., Cruz-Soriano, A. and Casas, A., 2024. Gathering, agriculture, and exchange: an ethnoecological approach to the study of food patterns and feedstuff sources in communities of the Central Andes, Peru. *Journal of Ethnobiology and Ethnomedicine*, *20*(1), p.69.

[10] Garrett, K.A., Bebber, D.P., Etherton, B.A., Gold, K.M., Plex Sulá, A.I. and Selvaraj, M.G., 2022. Climate change effects on pathogen emergence: Artificial intelligence to translate big data for mitigation. *Annual Review of Phytopathology*, *60*, pp.357-378.

[11] Cao, Z., 2025. Agent-Based Modeling in Agricultural Ecosystems: A Concise Review.

[12] Rosenheim, J.A., Cluff, E., Lippey, M.K., Cass, B.N., Paredes, D., Parsa, S., Karp, D.S. and Chaplin-Kramer, R., 2022. Increasing crop field size does not consistently exacerbate insect pest problems. *Proceedings of the National Academy of Sciences*, *119*(37), p.e2208813119.

[13] Weng, L., Tang, Z., Sardar, M.F., Yu, Y., Ai, K., Liang, S., Alkahtani, J. and Lyv, D., 2024. Unveiling the frontiers of potato disease research through bibliometric analysis. *Frontiers in microbiology*, *15*, p.1430066.

[14] Lugo Montilla, I. and Águas, C.L.P., 2025. Social technology and rescue of native seeds in the Venezuelan Andes Páramo. *Frontiers in Political Science*, *6*, p.1511955.

[15] Danielak, M., Przybył, K. and Koszela, K., 2023. The need for machines for the nondestructive quality assessment of potatoes with the use of artificial intelligence methods and imaging techniques. *Sensors*, *23*(4), p.1787.

[16] PAVEL, M., 2022. *INSECT PEST INFESTATION STATUS ON LOCAL POTATO VARIETY (LAL PAKRI) AND THEIR BIORATIONAL MANAGEMENT* (Doctoral dissertation, DEPARTMENT OF ENTOMOLOGY).

[17] Etherton, B.A., Choudhury, R.A., Alcalá Briseño, R.I., Mouafo-Tchinda, R.A., Plex Sulá, A.I., Choudhury, M., Adhikari, A., Lei, S.L., Kraisitudomsook, N., Buritica, J.R. and Cerbaro, V.A., 2024. Disaster plant

pathology: Smart solutions for threats to global plant health from natural and human-driven disasters. *Phytopathology®*, *114*(5), pp.855-868.
[18] Fuller, D.Q., Denham, T. and Allaby, R., 2023. Plant domestication and agricultural ecologies. *Current Biology*, *33*(11), pp.R636-R649.
[19] Zea, P., Pascual, C., García-Montero, L.G. and Cedillo, H., 2025. NDVI Performance for Monitoring Agricultural Energy Inputs Using Landsat Imagery: A Study in the Ecuadorian Andes (2012–2023). *Sustainability*, *17*(8), p.3480.
[20] Latorre, L., Bustamante, C., Riquelme, L., Muro, V. and Lugo, G., 2025. Report on Low-Risk Technological Solutions in Emerging Technologies in Agriculture.
[21] Lamichhane, S., Neupane, S., Timsina, S., Chapagain, B., Paudel, P.P. and Rimal, A., 2024. Potato Late Blight Caused by Phytophthora Infestans; an Overview on Pathology, Integrated Disease Management Approaches, and Forecasting Models. *Integrated Disease Management Approaches, and Forecasting Models*.
[22] Ligarda-Samanez, C.A., Palomino-Rincón, H., Choque-Quispe, D., Moscoso-Moscoso, E., Arévalo-Quijano, J.C., Huamán-Carrión, M.L., Quispe-Quezada, U.R., Muñoz-Saenz, J.C., Gutiérrez-Gómez, E., Cabel-Moscoso, D.J. and Sucari-León, R., 2023. Bioactive compounds and sensory quality in chips of native potato clones (Solanum tuberosum spp. andigena) grown in the high Andean region of Perú. *Foods*, *12*(13), p.2511.
[23] Saenz Lituma, M.G., 2022. *Using the Main Agroecological Structure (MAS) indicator for evaluating the agroecological status of farms along the ecuadorian northern-central Andean region* (Master's thesis, Padua, IT: Università Degli Studi Di Padova. Dipartimento di Ingegneria Civile, Edile e Ambientale).
[24] Saffer, A., Tateosian, L., Saville, A.C., Yang, Y.P. and Ristaino, J.B., 2024. Reconstructing historic and modern potato late blight outbreaks using text analytics. *Scientific reports*, *14*(1), p.2523.
[25] Cruz, M., Pradel, W., Juarez, H., Hualla, V. and Suarez, V., 2023. Deforestation dynamics in Peru. a comprehensive review of land use, food systems, and socio-economic drivers.