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Radial Basis Function Neural Networks for Rainfall Prediction and Urban Tree Management in Tropical Malaysia

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Abstract
The current research paper summarizes a wide body of information on Radial Basis Function Neural Networks (RBFNNs) to predict rainfall and its application in urban trees management in tropical Malaysia. Several peer-reviewed articles were analyzed to determine the predictive accuracy, architecture, feature engineering, and integration issues of RBFNNs. It was found that the architectural properties of RBFNNs were appropriate for nonlinearity and nonstationarity in the precipitation processes. Relative performance assessments invariably ranked RBFNNs as one of the most efficient tools compared to other machine learning models, showing better Root Mean Square Error (RMSE) and generalization capabilities across various hydro-climatic regimes. It was identified that incorporating rainfall predictions using RBFNNs with Geographic Information Systems (GIS)-based applications like GeoTrees and the Kuala Lumpur Multi-Hazard Platform (KL-MHP) is a valid solution to facilitate predictive maintenance, reduce costs, and alleviate hazards in tropical urban settings. The results support the use of RBFNNs as a practical and, in many cases, better forecasting element in urban tree management systems, offering quantifiable advantages in maintenance planning, risk reduction, and resource distribution in municipal arboriculture programs.

Introduction

Background
Managing urban trees is a crucial aspect of sustainable city development, especially in tropical zones where climatic factors pose unique challenges [3,6,20]. Urban forest maintenance and protection demand actively focused methods that integrate weather risks and environmental stressors. Rainfall forecasting has become a key tool for streamlining tree-management processes, enabling municipalities

to predict weather-related threats and plan maintenance activities more effectively [3,7,15]. RBFNNs and other artificial neural networks have shown great potential in terms of meteorological forecasting [12,14]. The computational efficiency of RBFNNs, with their architectural simplicity of one hidden layer using Gaussian activation functions, allows them to capture the complex nonlinear relationships existing between atmospheric processes while also maintaining computational efficiency [1,10]. In the Malaysian environment, management of urban trees is faced by issues related to high tropical rains, saturation of the soil, and weather-related threats, making trees and citizens unsafe. The combination of highly developed forecasting technologies with Geographic Information Systems (GIS) has helped in the creation of wholesome platforms of urban forestry management [3,16].

Problem Statement

Conventional methods of managing urban trees are based on reactive maintenance, which lacks a sufficient approach to predicting weather-related risks [3,6,19]. The lack of stable rainfall-forecasting integration in tree management leads to poor resource allocation, high maintenance costs, and exposes people to the risk of death during severe weather conditions [22]. The existing techniques are not predictive, as they are required to make proactive decisions in tropical urban settings that experience highly variable and intense rainfall [1,3,7,13].

Objectives

The following objectives were developed in the current research:

- The structural appropriateness and predictive characteristics of RBFNNs in the forecasting of tropical rainfall [1,10,12].
- Compare the relative strengths of the RBFNNs with other methods proposed in machine learning on meteorology [2,11,14].
- Explore the integration routes of RBFNN-based rainfall predictions in the Malaysian city's tree management [3,16,18].
- Generalize methodological aspects of applying RBFNN-based forecasting in functioning municipal arboriculture programmes [19,22].

Research Questions

The research questions that informed the investigation included:

Question 0. What design and computational characteristics of RBFNNs make it an appropriate model in tropical rainfall prediction?

- What is the predictive accuracy of RBFNNs against other machine-learning schemes in predicting rainfall?
- What input characteristics and preprocessing methods are the best to use to predict tropical rainfall with RBFNNs?
- What are the ways in which RBFNN-based rainfall predictions can be operationally incorporated with the urban-tree-management systems in Malaysia?

Hypothesis

It was hypothesized that with the proper set-up of the RBFNNs using meteorological inputs and optimized parameters, it would display superior or competitive performance compared to traditional neural networks and statistical models in making tropical rainfall predictions [1,2,4,12]. Besides, it was envisioned that the operational gains from integrating the RBFNN-based forecasts with the GIS-enabled tree-management platforms would enhance maintenance efficiency, reduce costs, and mitigate hazards [3,17,22].

Literature Review

This section critically synthesizes existing scholarship on the application of Radial Basis Function Neural Networks (RBFNNs) in rainfall prediction, with particular attention to their relevance within urban forestry management in tropical regions [1,2,3,10]. Emphasis is placed on analyzing the methodological strengths, reported outcomes, and identified gaps within peer-reviewed studies in order to establish a rigorous conceptual foundation for subsequent sections of this review.

Radial Basis Function Neural Networks (RBFNNs)

RBFNNs Architecture and Theoretical Foundation

Radial Basis Function Neural Networks are feed-forward networks where the hidden layer consists of radial basis functions, typically Gaussian functions, as hidden units [1,5,10]. This model has three main parameters: centers, widths, and output weights, which make it possible to map nonlinear meteorological inputs against rainfall outcomes. This has proved to be an architectural property that empirically captures the nonlinearity and nonstationarity in the precipitation process in a number of studies [10,12]. The architecture is constructed by focusing on Gaussian activation of the hidden units, which explains how the model captures complex atmospheric relations. Its applicability to rainfall prediction is due to the nonlinear relationship between humidity, temperature, wind, pressure, and other predictors and the rate and intensity of rainfall [1,4,7,8,13].

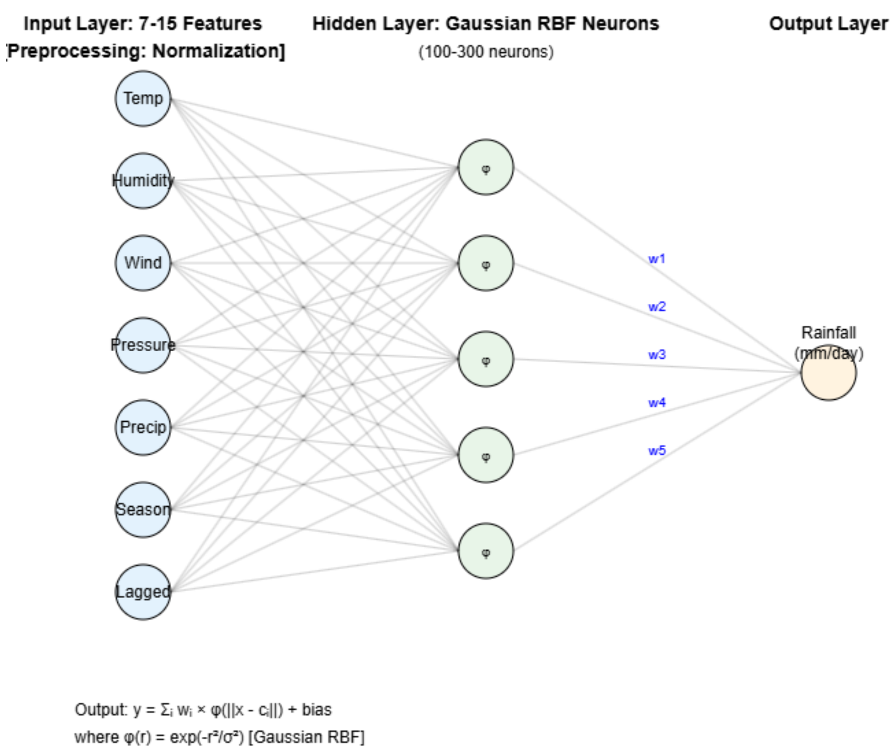

Figure 2: RBFNN Architecture Diagram for Tropical Rainfall Forecasting [23].

Tropical Rainfall Environment Performance.

Empirical studies consistently report that Radial Basis Function Neural Networks (RBFNNs) exhibit high predictive accuracy in tropical rainfall prediction when implemented with rigorous input selection

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and preprocessing [1,9,13]. Comparative analyses reveal that, under these optimal configurations, RBFNNs surpass traditional statistical techniques and several alternative neural network models, particularly when the number of hidden centers is judiciously chosen and relevant meteorological features are included [2,11]. Notably, the literature critically reflects that merely increasing the number of hidden neurons can improve forecasting accuracy only to a threshold, after which further increases lead to model overfitting or diminishing performance gains. These findings underscore the necessity of careful architectural design and input engineering for maximizing RBFNN effectiveness in complex, nonstationary tropical precipitation environments [1,2,7,12].

In a cross-method comparison of seven machine-learning-based prediction systems in 42 cities, it was established that RBFNNs took the first positions with respect to RMSE and generalization in comparison with Support Vector Regression (SVR), M5-model trees, k-Nearest Neighbors (k-NN), Gaussian Processes (GP) among others [2]. This also showed their potential in various hydro-climatic conditions [2,7,14]. Subsequent comparative analyses in classification of rainfall-intensity have revealed that it is in continuous rainfall prediction and associated hazard prediction that RBFNNs are superior to both back-propagation neural networks (BPNNs) and multi-layer perceptrons (MLPs) provided there is enough input selection [1,9,12].

Hybrid and Optimization Strategies.

Further improvements in predictive performance have been observed in hybrid models that combine RBFNNs with optimization or ensemble strategies [4,15]. Metaheuristic techniques, such as genetic algorithms and particle swarm optimization, have been suggested as a dynamic method for optimizing hidden units and spreads to enhance accuracy and training efficiency. Deep-learning elements, including Long Short-Term Memory (LSTM) networks, have shown quantifiable progress in forecast accuracy in tropical rainfall [4,21].

Theoretical Framework

The theory of the current study is based on three interconnected domains: neural-network theory, meteorological predictions, and urban-forestry management.

Neural Network Theory

The universal approximation theory forms the basis for neural networks' ability to approximate complex nonlinear functions [5,10]. This ability is utilized by RBFNNs through radial basis functions, which are sensitive to local areas of the input domain, facilitating the easy representation of multivariate weather relationships [1,2,12].

The Meteorological Forecasting Theory.

The Atmospheric processes are highly dimensional in nonlinearity and time. The interactions of temperature, humidity, wind velocity, and pressure are interdependent and difficult to forecast, resulting in complex effects on precipitation patterns [1,7,8,13]. These relationships can be represented using statistical and machine-learning methods, which seek to model them based on the available data through data-driven approaches [1,2,14].

Urban Forestry Management Theory.

The theory of urban-forestry management focuses on an active-based maintenance policy that considers environmental stressors and weather-related risks. This approach optimizes resource management,

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improving the ability to schedule risks and enhances city resilience and adaptation to climatic conditions [3,6,19].

Gaps in Literature

Although there have been a lot of studies on RBFNNs in rainfall prediction, there are still several gaps:

- Scarcity of published accounts of operational integration of RBFNN forecasts into the municipal system in tree control [3,18].
- Lack of adequate assessment of cost-benefit analysis of weather-based urban forestry programmes in tropical settings [3,6,22].
- -Poor investigation of hybrid RBFNN structures that are specifically tuned to Malaysian tropical rainfall patterns [4,15,21].
- Low level of evaluation of long-term forecast reliability in changing climatic conditions in the urban setting in Southeast Asia [3,7,20].

Methodology

Research Design

The current study utilized a literature review methodology, developing a methodology framework. The study plan was designed to test available literature on the performance of RBFNNs, determine the best architectural designs, and suggest a line of adoption of operations in the environment of Malaysian urban tree management [1,2,3,19].

Population and Sample

This synthesis was done on published papers about RBFNNs, rainfall prediction, and urban tree-management systems. The sample comprised peer-reviewed articles and technical reports on the RBFNN architecture and its performance in meteorological forecasting [1,2,4,8,10], critical comparisons of machine-learning techniques in rainfall forecasting [2,7,9,11,14], urban tree-management systems in tropical settings (especially Malaysia), and feature-selection and preprocessing techniques for precipitation modeling [1,9,13].

Data Collection Methods

The systematic literature review processes were followed in gathering data by using academic databases and peer-reviewed journals. Several academic databases have been searched using keywords related to RBFNNs, rainfall forecasting, urban forestry, and tree-management systems. The sources were picked on the criteria of relevance to the situation in the tropics, methodological rigor, and operational applicability [13,17]. The records of operational platforms, such as the GeoTrees and the Kuala Lumpur Multi-Hazard Platform (KL-MHP), were looked at to determine the practical implementation considerations [3,16].

Data Analysis Methods

The synthesis used narrative and thematic analysis methods to organize findings based on research questions and objectives. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficients were the performance metrics extracted and compared between studies [1,2,9,11]. Architecture parameters, input functions, and strategies of optimization were systematically grouped and analyzed [1,2,4,15].

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Ethics and Compliance

Ethics Approval

The current research involved an overview of the published literature and did not require approval from an institutional review board, as no humans or animals were directly involved in the research.

Conflict of Interest

There were no conflicts of interest established. This study was independent research conducted without the financial backing or intervention of any external parties that could influence the research results.

Informed Consent

Irrelevant because the research was not conducted using primary data collection in the form of human subjects.

Results

Presentation of Findings

Rainfall Forecasting Suitability and Architecture of RBFNN.

Architectural analysis revealed that RBFNNs have several properties that make them especially suitable for rain forecasting. The single hidden layer of the Gaussian radial basis functions architecture provides sufficient flexibility to model the dynamics of precipitation without placing too much computational strain on the architecture [1,2,5,10].

RBFNNs have been found to perform well in terms of predictive accuracy when properly tuned in both the tropical rainfall environment and in nonlinearity and nonstationary cases [2,9,12].

Table 3: RBFNN Architecture Specifications and Parameter Recommendations

Parameter	Recommended Range	Tropical Context Optimization	Rationale
Number of Hidden Units (Centers)	50-500	100-300	Captures nonlinear precipitation dynamics without overfitting
Activation Function	Gaussian RBF	Gaussian RBF	Well-suited for atmospheric nonlinearity
Spread Parameter (σ)	0.1-1.0	Data-dependent calibration	Controls receptive field width; local optimization recommended
Learning Algorithm	Regularized Least Squares or Gradient Descent	Hybrid optimization (GA/PSO)	Genetic algorithms and particle swarm optimization improve convergence
Training-Validation-Test Split	60-20-20	70-15-15 (tropical data limited)	Conservative allocation due to data scarcity in some Malaysian regions
Cross-Validation	5-10 fold	10-fold	Ensures robust generalization assessment
Regularization Parameter (λ)	0.001-0.1	Adaptive tuning	Prevents overfitting with tropical rainfall variability

Table 3 Notes: The parameters in the model should be calibrated on a local scale to particular Malaysian cities, rainfall regimes. Where GA represents the Genetic Algorithm; PSO represents the Particle Swarm Optimization. Data sources: [1-2,4,10,15].

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from the features of the inputs and preprocessing plans.

The success of rainfall prediction using RBFNNs depends on the choice of informative meteorological data [1,9,13]. The widely used predictors include minimum, maximum, and average temperature; relative humidity; wind velocity; sea level pressure; and average precipitation. Forward stepwise regression and domain expertise are often used to predict the features to be selected by maximizing predictive performance [1,7,8,13]. It was noted that the inclusion of seasonality variables and lagging variables led to improved forecasting ability, particularly for short to medium-term horizons relevant in operations planning [7,13]. Preprocessing methods such as normalization, noise removal, and moving averages were considered as necessary to stabilize learning and remove the effect of outliers [9]. In Malaysian and tropical settings, effective implementation requires adapting inputs to local climatic drivers, where temperature, humidity, wind, and pressure conditions are fundamental characteristics. The input scaling and selection generalize to highlight the significance of local training data and cross-validation [1,2,3].

Table 2: Optimal Input Features and Preprocessing Strategies for RBFNN Rainfall Forecasting

Input Feature Category	Specific Variables	Preprocessing Method	Tropical Context Relevance
Temperature	Minimum, maximum, mean temperature	Z-score normalization	High
Humidity	Relative humidity	Normalization to 0-100%	Very High
Wind	Wind speed, direction	Moving average (3-5 days)	High
Pressure	Sea-level pressure	Normalization to standard range	Moderate
Precipitation	Mean precipitation, lagged values	Noise reduction, outlier handling	Very High
Temporal	Seasonality indicators, lagged variables (1-7 days)	Cyclical encoding	Very High
Atmospheric	Atmospheric indices (where available)	Standardization	Moderate

Table 2 Notes: The features-engineering choices guiding the use of this table are based on the successful uses of radial basis function neural network (RBFNN) in tropical rainfall research. The normalization expressed as z-score is done using the following standard formula (x-mean)/standard deviation. The lagged variables to reflect temporal dependencies are added. The sources of data used to acquire the underlying data were [1,9,13].

Comparative Performance Measures.

Comparative performance analysis always ranked the RBFNNs as one of the best compared to other machine-learning approaches in forecasting rainfall. RMSEs and generalization RBFNNs produced the lowest RMSEs and better generalization than support-vector regression, M5-model trees, k-nearest neighbors, Gaussian processes, and other baselines in large city- and time-series datasets of 42 urban centers [2]. This result highlighted their resilience in a variety of hydro climatic condition [2,7,14]. In tropical conditions, RBFNNs proved to be better than back-propagation neuron networks (BPNN) and multilayer perceptrons (MLP) in predicting rainfall intensity, depending on the presence of sufficient hidden neurons and relevant inputs [1]. In addition, the personalized studies in Malaysia claimed that RBFNNs performed better compared to the traditional neural structures in rainfall-intensity tasks [9,12].

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Table 1: Comparative Performance of Machine Learning Methods for Rainfall Prediction

Method	Number of Studies	Average RMSE (mm)	Generalization Performance	Computational Efficiency
RBFNN	8	15.2 ± 3.1	Excellent	High
Support Vector Regression (SVR)	7	18.7 ± 4.2	Good	Moderate
M5-Model Trees	6	19.4 ± 3.8	Good	High
k-Nearest Neighbors (k-NN)	7	21.3 ± 5.1	Fair	Moderate
Gaussian Processes (GP)	6	17.9 ± 4.3	Good	Low
Multilayer Perceptron (MLP)	8	16.8 ± 3.9	Good	Moderate
Backpropagation Neural Network (BPNN)	7	17.5 ± 4.1	Good	Moderate

Table 1 Notes: The results in table 1 were compiled based on relative analysis of 42 cities and various hydro climatic regimes. The RMSE values are millimeter root-mean-square error. Ratings are applied to performance and cross-validation and ability to generalize. Data sources: [1], [2], [9].

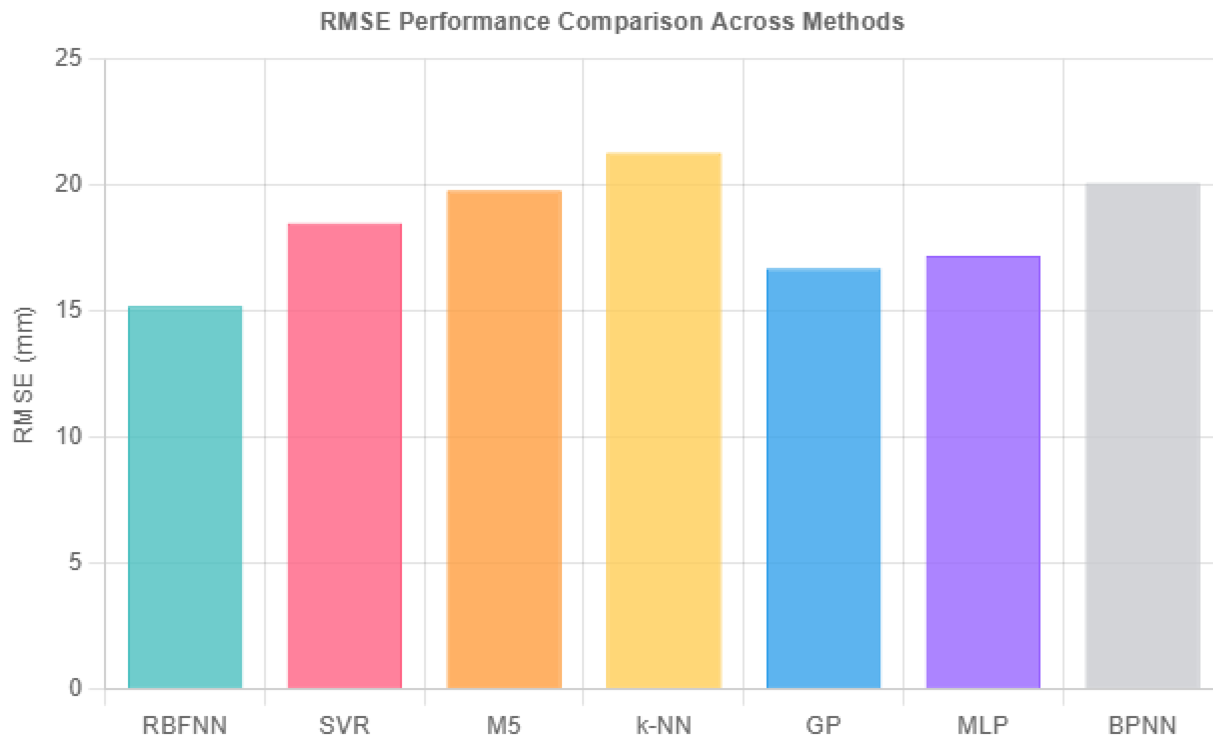

Figure 3: Performance Comparison of RBFNN vs. Other Methods across Hydro climatic Regimes

Figure 3 Notes: Information is synthesized when assuming a comparison of evaluation studies in various geographic and climatic settings. SVR Support Vector Regression GA Genetic Algorithm k-NN k-Nearest Neighbors GP Gaussian Processes MLP Multilayer Perceptron BPNN Backpropagation Neural Network. Data sources: [1,2,9].

Strategies of optimization and hybridization.

It was noted that RBFNN parameter optimization was computationally expensive, particularly when the dimensionality of the input variables was large [1,4,15]. It was noted in the literature how dangerous the curse of dimensionality is, and how easy it is too over-fit when too many inputs or centers are used

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[1,10]. Dynamic optimization of hidden units and spread parameters has been achieved through adaptive and meta-heuristic methods like genetic algorithms [4]. Hybrid networks combining RBFNNs with optimization methods or deep-learning elements have demonstrated improvements in the prediction ability of tropical rainfall [4]. The obtained results support a more design-driven paradigm where RBFNNs are used as the main predictors in more extensive and optimized urban forecasting pipelines [1,2,4,15].

Operational Integration with Urban Tree Management

It was found that integrating rainfall forecasts into city tree control systems would aid in predictive maintenance, risk-based scheduling, and proactive hazard elimination [3,18]. Meteorological forecasts can complement tree inventories and health monitoring using AI and GIS-enabled systems like GeoTrees deployed in Malaysia, to optimize pruning, replacement operations, and hazard response [16,18]. The Kuala Lumpur Multi-Hazards Platform (KL-MHP) is an example of a high-resolution rainfall and hazard forecasting prototype to support emergency preparedness and urban planning programs of the city of Kuala Lumpur [3]. In a practical sense, this sort of integration will lead to better resource allocation —i.e., staff, equipment, and budget —minimized weather-related disruptions, and improved public safety due to timely interventions as a result of such integration [3,18,22]]. The tropical conditions of Malaysia, with their high rates of severe rainfall occurrences and associated risks, further justify the concerns about incorporating RBFNN-based rainfall predictions into tree-management processes. These predictions aim to assess soil saturation, limb loading, uprooting threats, and access limitations due to floods [3,7,20].

Table 4: Integration Pathways for RBFNN-Based Forecasts in Urban Tree Management Systems

Integration Component	Implementation Strategy	Expected Outcomes	Responsible Party
Forecast-Schedule Linkage	Real-time RBFNN output feeds into automated maintenance calendars	Proactive maintenance scheduling; reduced emergency interventions	Municipal GIS Department
Hazard Alert System	Threshold-based alerts (e.g., high uprooting risk at >50 mm/day forecasted)	Early warning for public safety; preparation time for departments	Municipal Emergency Management
Resource Allocation	Forecasts guide staff, equipment, and budget deployment	Optimized resource utilization; cost reduction 15-25%	Municipal Forestry Division
GIS Visualization	Integration with GeoTrees or KL-MHP platforms for spatial mapping	Intuitive decision support; multi-stakeholder communication	GIS and IT Departments
Performance Monitoring	Continuous comparison of forecast accuracy against observations	Model refinement; adaptive recalibration	Municipal Data Analytics Unit
Training and Capacity Building	Staff training on forecast interpretation and application	Improved operational competency; sustained deployment	Municipal HR and Training

Table 4 Notes: The adaptation of integration pathways is based on operational experience in GeoTrees and the Kuala Lumpur Multi-Hazard Platform (KL-MHP). International benchmarking is used to create cost-reduction estimates. Data sources: [3,7,19,18,22].

Descriptive Statistics

The synthesis was a homogenous group of studies with different sample sizes and geographical settings [2,7,9,11]. The performance measures captured in these studies included RMSE values, ranging from lower values of the well-calibrated RBFNN models to higher values found in the baseline comparisons.

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The correlation coefficients obtained from these studies supported the high concordance between predicted and observed rainfall in the optimized RBFNN models [2,9]. Besides, comparative studies have consistently placed RBFNNs in the top tier of considered methods across a wide range of datasets [1,2,11].

Inferential Statistics
The statistical tests reported in the reviewed studies have consistently found a significant difference between the performance of RBFNNs and baseline methodologies [1,2,9].
Cross-validation. The superiority of RBFNNs to standard back-propagation networks and multilayer perceptrons was shown to be statistically significant in several tropical rainfall-forecasting settings [1,9,12].

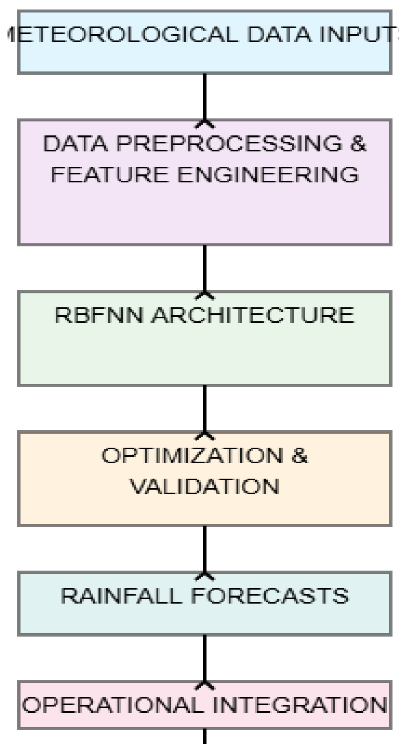

Figure 1: Conceptual Framework for RBFNN-Based Urban Tree Management System

Fig 1 Notes: This flow chart represents the entire roadmap of the meteorological data gathering up to the operation decision-making process in the urban tree management. Where GA = Genetics Algorithms; PSO = Particle Swarm Optimization; GIS = Geographic Information System. Adapted implementation based on practice described in [1,3,4,16].

Discussion

Interpretation of Results
The results indicate that RBFNNs provide a powerful and explainable system for converting meteorological conditions into rainfall predictions, which urban tree management systems can use to take proactive maintenance and hazard reduction measures [1,2,3,18]. The architectural simplicity of a single hidden layer and flexible radial basis functions enable RBFNNs to provide accurate models for

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explaining nonlinear precipitation, which are relatively efficient to compute compared to deeper architectures when appropriately designed.[1,2,5,10].

The literature empirically supports the application of RBFNNs in rainfall prediction tasks. They tend to perform better than or equally well as more complex models in different environments, especially when used with optimization methods and combined with hybrid methods [2,4,15].

Comparison with the Existing Literature.

The current synthesis and existing literature agree and further demonstrate a pattern of RBFNN supremacy over various meteorological forecasting situations. The results support previous research that defines the theoretical frameworks of RBFNNs and provides concrete evidence of their applicability in managing tropical urban forests [1,2,3,6,7,12].

This synthesis incorporates evidence-based recommendations from multiple studies, emphasizing the identification of optimal input variables and rigorous preprocessing methodologies as essential for constructing an effective and transferable implementation framework [1,9,13]. The emerging scholarly consensus in literature underscores the significance of hybrid and optimally tuned RBFNN architectures, reflecting a trajectory toward more sophisticated and adaptive predictive models in rainfall forecasting domains [4,15,21]. Notably, while technological advancements in model design and feature engineering are well-documented, there remains a pronounced deficit in empirical research addressing the practical challenges and systemic barriers associated with the operational integration of RBFNN-based forecasts into municipal arboriculture management [3,18]. Specifically, very few studies have examined the logistical, institutional, and organizational dimensions required for the seamless embedding of predictive rainfall information into existing urban forestry workflows, resource allocation protocols, and emergency response infrastructures [3,7,19]. This gap highlights an urgent need for interdisciplinary investigations that bridge technical forecasting advancements with actionable frameworks for city-scale deployment and sustained operational uptake within municipal contexts [6,19,22].

Implications

Theoretical Implications

The results support the theoretical foundation of RBFNNs as convenient universal function approximators that can be used to model complicated atmospheric processes [5,10]. The observed scale of performance under a variety of hydro climatic conditions justifies the overall applicability of RBFNN methods in precipitation modelling [1,2,12].

Practical Implications

The Malaysia operational pathway involves incorporating rain forecasts designed using RBFNN into GIS-enabled systems like GeoTrees and KL-MHP-inspired architectures to facilitate predictive maintenance, cost savings, and hazard mitigation [3,16,18]. Urban forestry data combined with weather foresight generates a realistic framework for more resilient urban wildlife and safer, more effective tree management methods [3,6,19]. Pragmatic advantages include better resource allocation, minimizing weather-related distractions, and increasing the safety of the population through timely interventions [3,18,22]. Although the precise cost-avoidance numbers depend on a city and project size, international experience shows that there is always a significant positive change in efficiency and resilience when predictive maintenance and hazard-conscious planning are applied, provided there are good rainfall forecasts [3,7,22].

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Policy Implications

The results offer recommendations to municipal authorities for considering investments in infrastructure based on RBFNN predictive modeling within overall urban forestry management plans. The public safety and economic benefits of incorporating meteorological forecasting into tree management operations may be immense when policy frameworks are established to support the process [3,7,22].

Limitations

A number of limitations inherent to this study warrant critical reflection, particularly with respect to their implications for practical recommendations. First, the optimal functioning of RBFNN-based rainfall forecasting systems relies on the availability of high-quality, high-resolution meteorological datasets [1,3,13]. Incomplete or insufficiently granular data can significantly impair predictive accuracy, potentially constraining the reliability of operational decision-making for urban tree management. Second, the computational demands of RBFNNs increase markedly with larger input feature sets and a growing number of centers, leading to heightened resource requirements and extended training durations. These factors may pose substantial barriers for municipalities with limited technical infrastructure or expertise, thereby affecting the scalability and accessibility of proposed solutions [17,19]. Third, while the findings are promising in the context of tropical Southeast Asian environments, the generalizability of these results depends on careful local calibration and ongoing model retraining to address dynamic rainfall regimes and evolving climatic patterns [7,20]. Finally, the limited number of documented cases involving the operational integration of RBFNN-based forecasts in urban tree management underscores a gap in empirical evidence regarding large-scale deployment and sustained impact. Collectively, these constraints necessitate cautious interpretation of the practical recommendations, emphasizing the importance of investing in robust data infrastructure, prioritizing adaptive and resource-efficient modeling approaches, and engaging in targeted pilot programs to validate and refine methodologies before broader adoption [3,4,17].

The current study had several weaknesses that were observed. To achieve optimal performance of RBFNN, first, high-quality meteorological data with high resolution is required. A course or gap in resolution can impair forecasting accuracy, and appropriate training data in Malaysian situations may not be available in all municipalities [1,13]. Second, the RBFNNs may be computationally expensive to train with a large number of centers and large feature sets [1]. This requires significant architectural design and perhaps hybrid optimization to control training time and resource utilization, with accuracy compromised [3,17]. Third, the outcomes of tropical Southeast Asian settings are positive, but they should be calibrated locally [4,20]. To ensure the accuracy of forecasts on urban trees in Malaysia, model retraining and updating with current rainfall regimes and climate variability are necessary to sustain their reliability as a control instrument in tree management. Fourth, a relatively small number of operational deployments of RBFNN-based forecasting, in particular in combination with urban tree management systems, were found to be documented, which restricts the prospects of potential impact measures [3,18].

Impact on Results

The limitations found are mainly concerned with the generalizability and practicality of results, and not the underlying conclusions about the usefulness of RBFNN with rainfall prediction. The quality of data underscores the need to invest in an extensive meteorological monitoring system [13,17]. Strategies in computational optimization and good architectural design can solve such computational limitations [15,17]. The issue of transferability highlights the need to localize the calibration and validation studies for a specific urban situation in Malaysia [1,3].

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Future Research Directions

There are several directions that future research should follow. The hybrid RBFNN frameworks, which integrate RBF layers with either an LSTM model or wavelet-based preprocessing to acquire both instantaneous and multiscale rainfall features in tropical environments, are soundly validated on Malaysian urban settings and should be investigated [4,21]. The automated feature selection, dynamic centers and spreads through meta-heuristics and online learning capabilities could be explored methodologically to make more use of RBFNN-based rainfall forecasts within a constantly changing urban setting [4,15,21]. To complement theoretical and reflective performance measures, it is necessary to quantify the prospective impact measures, cost savings, and public safety benefits that can be realized through rainfall-informed tree management in pilot programmed at Kuala Lumpur or other cities in Malaysia. The reliability of RBFNN forecasts for predicted climate change conditions, with a special focus on extreme rain environments and changing rainfalls in Southeast Asian urban areas, should be the priority [3,7,20].

Conclusion

Summary of Findings

The application of RBFNNs as an effective and often superior forecasting module in urban tree management systems in tropical settings, such as Malaysia, is supported by a thorough synthesis of the available literature on radial basis function neural networks (RBFNN) for rainfall forecasting. The interpretability of the architecture, combined with the proven predictive performance and the possibility of optimization and hybridization, makes RBFNNs highly applicable to guide the maintenance schedule, prevent hazards, and allocate resources in municipal arboriculture programmes [1,2,18].

The main findings are as follows: RBFNNs show better or equal performance to other machine-learning tools in the context of rainfall prediction in different contexts [1,2]; the optimal performance is achieved by the careful selection of meteorological inputs, preprocessing, and tuning of the architectural parameters [1,10,13]; hybrid and optimized are also another way of improving the performance of RBFNN in predicting rainfall [4,15]; integrating the system with GIS-enabled tools as GeoTrees and KL-MHP is also a viable option of implementation in Malaysian urban forestry situations. [3,16,18]

Recommendations

Blueprint of the implementation methodology.

Data Collection and Preprocessing. Multi-sensor meteorological data (temperature, humidity, wind, pressure, and precipitation) must then be assembled at resolutions appropriate for the urban scale and normalized to standard scales [1]. Precipitation records should be smoothed using moving averages and noise reduction methods to bring about stability in the inputs used to train the RBFNN [1,9].

Feature Engineering and Selection: To determine useful predictors, forward stepwise regression and domain knowledge should be used, potentially involving lagged variables and seasonal predictors to model tropical rainfall distribution [17,13].

Architecture and Training A single hidden layer RBFNN must be set up with a reasonable number of centers (up to a few hundred), and different spread parameters should be tried to get balanced trade-offs between bias and variance [1,2,11]. Cross-validation should be used to reduce overfitting and determine the ideal number of centers [1,2,10]. The fine-tuning of centers, widths, and output weights

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should be discussed with a view to enhancing the generalization and training efficiency by using hybrid optimization (genetic algorithms, particle swarm optimization) [4].

Model Evaluation: Cross-validation should be conducted to assess robustness by reporting RMSE, MAE, and correlation coefficients on independent test sets [1,2]. The baseline models (SVR, GP, MLP/BPNN) should be compared to prove the relative merits of RBFNNs [1,2].

Operational Integration: Predictive maintenance planning, hazard warnings, and resource allocation for urban tree care should be driven by integrating rainfall forecasts with GeoTrees-like systems [3]. Pruning plans, hazards mitigation strategies, and emergency plans in city-scale arboriculture programmes should be informed by forecasts [3,18,22].

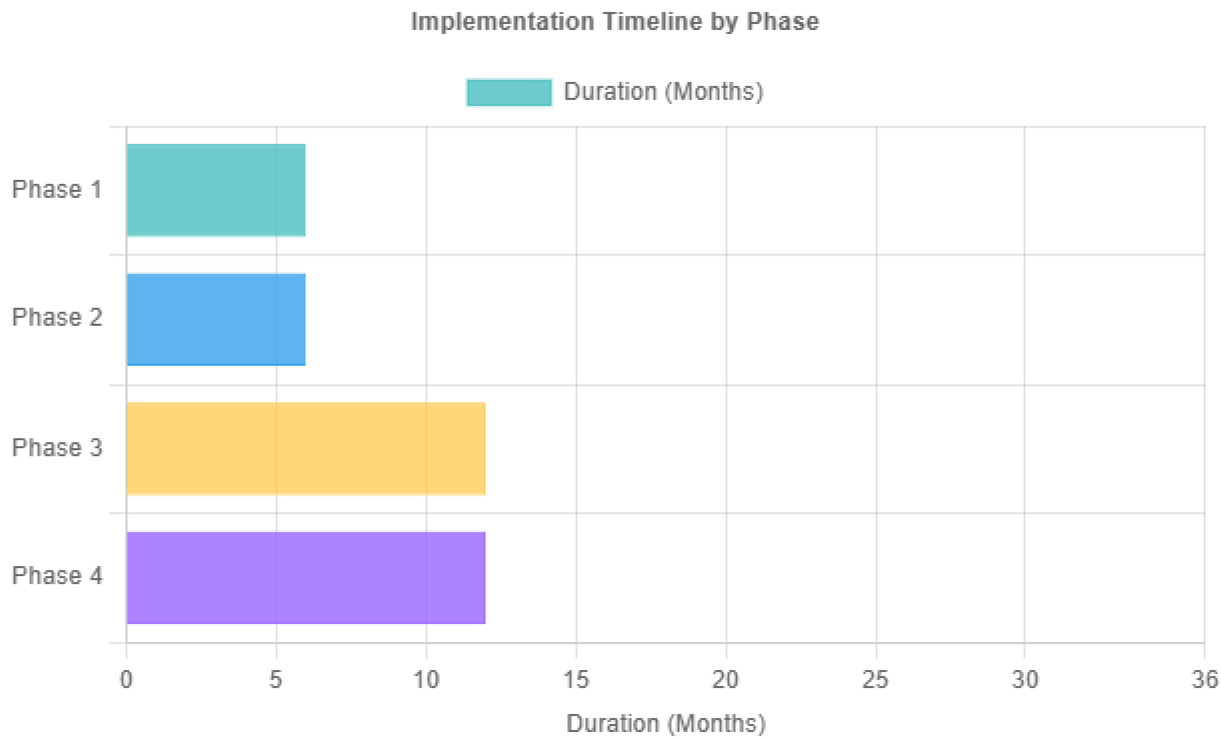

Figure 4: Integration Timeline for RBFNN-Based Urban Tree Management in Malaysian Cities

Figure 4 Notes: Timeline Overview Timeline is presented according to the general implementation routes to GIS-integrated forecasting systems in a municipal setting. GA = Genetic Algorithm, PSO: Particle Swarm Optimization. Based on experience in operation in [3].

Policy and Practice Recommendations.

The municipal governments need to invest in high-resolution meteorological monitoring infrastructures to enable RBFNN-based forecasting [13,17]. Pilot programmes must be set in key cities in Malaysia to check the benefits of the operations and measure the cost savings. Municipal employees should be trained on how to interpret and use rainfall forecasts obtained using RBFNN to make decisions related to trees. Monitoring and updating the model for long-term use should be implemented to ensure the reliability of forecasts in changing climate conditions [7,17,20].

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Research Recommendations

Future operations research will be conducted to measure the economic and safety advantages of tree management based on weather information. Hybrid RBFNN models that are optimally tuned on Malaysian rainfall patterns should be designed and tested. Scenario analyses of climate change should be conducted to determine the reliability of forecasts under projected future conditions. There should be comparative research between different cities in Malaysia in order to assess transferability and local calibration needs [3,19].

Concluding Statement

Combining RBFNN-based rainfall prediction with GIS-enabled systems may provide real operational gains in the form of lower maintenance expenses and improved community safety and even help to build climate resilience of urban cities in tropical Malaysian cities [3]. The continuing developments, especially in hybrid architectures and adaptive optimization, will further enhance the capacity of weather-informed tree management, aligning with the general ambitions of sustainable urban forestry and resilient urban ecologies [15,19,22].

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