International Journal of Industrial Engineering
2025;9(1):1-8.
ISSN: 2456-8449

IoT-Enabled Green Roof Management with RNN-Based Dynamic Environmental Control

N. L.Venkataraman[1*], S. Sumithra[1], S. SureshKumar[1], R. Purushothaman[1], K. Kukulavani[1], V.Gowri[1]

[1]*Department of Electronics and Communication Engineering, J.J.College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India.*

[*]*Corresponding author: venkat.altera@gmail.com*

Abstract. This research presents a dynamic environmental management system for urban landscapes that leverages Recurrent Neural Networks (RNNs) in the context of IoT-enabled green roof management. Green roofs play a pivotal role in promoting urban sustainability by improving air quality, mitigating urban heat island effects, and enhancing energy efficiency. The proposed system integrates a network of environmental sensors—measuring temperature, humidity, light intensity, soil moisture, and air quality—to continuously monitor and optimize the performance of green roofs. The collected sensor data is processed using an RNN model, which is particularly well-suited for this application due to its ability to capture temporal dependencies and trends in sequential data. By forecasting environmental conditions, the RNN provides insights into the operational health and effectiveness of green roofs. Moreover, the system supports real-time decision-making by offering adaptive recommendations for controlling ventilation, lighting, and irrigation systems. This dynamic feedback mechanism not only reduces energy consumption but also strengthens the overall sustainability of urban environments. Experimental evaluations demonstrate that the RNN-based approach achieves superior accuracy, precision, and recall compared to conventional models. These findings highlight the potential of combining IoT technologies with advanced machine learning to optimize urban green infrastructure. The study underscores the broader significance of such intelligent systems in advancing sustainable urban development and in enhancing the resilience of cities to environmental challenges.

Keywords: Urban Sustainability, Environmental Monitoring, Recurrent Neural Network (RNN), Internet of Things (IoT), Green Roofs, Energy Efficiency

INTRODUCTION

Buildings with green roofs and thermal insulation have been the subject of experimental study in this article. The study found that green roofs with thermal insulation give the highest thermal performance when compared to conventional, green and traditional roofs in a school building in the Gaza Strip [1]. Based on LiDAR data and information from the vegetation index cadaster, land surface temperature, and impermeability cadaster, this research outlines a technique for sustainable development that estimates the potential of green roofs and prioritises appropriate areas using a digital surface model [2]. Using a quasi-experimental approach, the study found that green roofs in cities had widely varying cooling performances [3]. Policymakers may use this inexpensive method to assess green roof schemes' ability to reduce urban heat. Research on the impacts of green roofs on climate in Mediterranean cities in Chile found that they lower temperatures in Concepción and lessen the energy generated by turbulent Kinect, hence reducing the severity of heat island effects [4]. Despite promises of increased output, rooftop solar power plants are seeing their efficiency deteriorate. An examination of a 500.3 kWp system reveals a decline in yearly energy production [5]. Green power and capturing generation loss: a suggested methodology.

University College Dublin (UCD) in Dublin, Ireland is home to four green roof installations. This study uses modern sensors to capture meteorological and hydrological data from each roof, improving upon standard assessments [6]. Using rainfall hyetographs, the extensive dataset allowed for precise parameter modelling of runoff hydrographs, which were then evaluated by advanced machine learning techniques. Urban regions see an increase in CO_2 uptake due to green roofs. Using long-term data from the huge green roofs at Berlin-Brandenburg Airport, machine learning can estimate the net ecosystem exchange (NEE) across many years [7]. In this research, we look at how weather forecasts affect NEE prediction and transferability. Improved comprehension of VR performance dynamics, optimisation of design parameters, and promotion of sustainable urban settings are all goals of this work, which investigates the use of AI and ML in VRs modelling [8]. The study's overarching goal

Received: 09-09-2024 Revised: 26.11.2024 Accepted: 19.12.2024

is to provide novel methods for sustainable urban stormwater management by combining real-time data with ML algorithms.

To address these challenges, there is growing interest in leveraging Internet of Things (IoT) and Artificial Intelligence (AI) technologies to optimize green roof monitoring and management. IoT systems employ sensors, actuators, and communication technologies to capture and transmit real-time environmental data. In the context of green roofs, IoT sensors can monitor variables such as temperature, humidity, soil moisture, and solar radiation, transmitting the data to centralized control systems or cloud platforms for advanced analysis. The vast amount of data generated by IoT-enabled systems necessitates the use of machine learning (ML) and deep learning (DL) models to extract meaningful insights. RNNs are particularly well-suited due to their capacity to model sequential and time-series data. RNNs retain prior information in hidden states, enabling them to capture temporal dependencies and trends. This makes them highly effective for tasks such as time-series prediction, anomaly detection, and dynamic system control, all of which are essential for adaptive green roof management.

Data on the effects of green roofs on urban ecology and architectural design were gathered using the Delphi method and remote sensing technologies in this study [9]. The impact of thermal comfort on interior settings was assessed using the CASBEE approach and a CNN-LSTM hybrid model. Research on PV-GR and agricultural photovoltaic modules is the primary emphasis of this literature review on solar photovoltaic modules and greenery co-location systems [10]. Its goals are to figure out how much coverage there is for climate change, what those advantages are, and to provide a thorough performance evaluation. We provide MOO-GPANN as a solution to the problems with approaches based on fuzzy frameworks for optimising green roof designs [11]. By processing, feature selecting, and predicting using GPANN can outperform previous models utilising data from NYC Green Roof Footprints. To optimise the design and operation of green roofs in buildings, this study presents a new smart energy-comfort system for green roofs in housing estates. The system uses integrated machine learning (ML), Design Builder (DB) software, and Taguchi design calculations [12]. For appropriate green roof parameters, the optimising approach maximises thermal comfort and energy conservation for green roof structures.

The leaching of nitrogen and phosphorus from the soil-like base makes green roofs potential sources of pollution. Soil addition biochar can boost plant performance and decrease nutrient runoff [13]. It has little effect on the amount of water that is retained. Energy dynamics in city planning relate to green infrastructure components [14]. Various case studies from different places are presented, with an emphasis on the real-world consequences for better insulation, less heat transfer, and optimised energy use. To better understand how rooftop plantings affect air quality in Lahore and Faisalabad, our study used an agro-ecological framework [15]. Dust samples were taken at random from various locations with or without plant cover, as well as from bare rooftops, and an optoelectronic sensing device was utilised to record the quantity of particulate matter. Heavy metal detection was then performed on these samples. The purpose of the study was to determine whether 16 substantial green roofs located in four different Norwegian cities could be adequately estimated using single-site calibration [16]. According to the results, parameters were ideal for one site but performed badly for the others when calibrated on a single site. By calibrating at many locations, we were able to use a standard set of parameters that worked well across all our sites and roof types.

A green roofing hybrid prediction model that combines VMD, TCN, and GRUs [17]. To overcome the difficulties in modelling complicated structures and to facilitate future research, this model correctly forecasts the thermal insulation performance of complicated green roof designs. Through a comprehensive analysis of the variations in the roofs' physical features, environmental consequences, and performances in relation to their attributes, this study aims to lay the groundwork for optimising green roof designs [18]. The research uses 2D and 3D urban morphological factors to model the cooling effects of green roofs in downtown Austin, Texas [19]. Using eleven different neural network techniques, it probes the relationship between DLST and city characteristics. Living green roof and wall systems are the focus of this investigation on their thermal efficiency in cold climes, with a focus on Quito's 4C climate [20]. By controlling interior thermal conditions, maintaining temperatures, and withstanding bad weather, these systems prove to be resilient, according to the study.

PROPOSED METHODOLOGY

This study is designed to achieve the following objectives:

1. **Enhance green roof management** through the deployment of IoT-based sensors for real-time data acquisition and intelligent environmental control.

2. **Leverage Recurrent Neural Networks (RNNs)** to accurately forecast environmental variables and enable adaptive modification of green roof systems.
3. **Promote plant vitality** by maintaining optimal levels of soil moisture, temperature, humidity, and light on green roofs.
4. **Improve urban energy efficiency** by utilizing green roofs as a natural temperature regulator, thereby mitigating the impacts of urban heat islands.
5. **Ensure sustainable resource utilization** by employing data-driven decision-making to reduce water consumption, minimize resource waste, and support long-term green roof maintenance.

This method demonstrates a sustainable approach to managing urban landscapes. The process begins with the acquisition of green roof sensor data, which includes temperature, soil moisture, light intensity, humidity, and other plant health indicators. To ensure data consistency and comparability, the raw sensor readings are preprocessed through data cleaning, missing value imputation, and feature normalization. Following data preparation, a task-specific RNN architecture is developed. Since the data is sequential and collected at regular intervals, the RNN can effectively capture temporal dependencies and forecast future environmental conditions. To handle long sequences and address the vanishing gradient problem, advanced variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) are employed.

Once the architecture is established, the model is trained using the preprocessed data. During training, the algorithm predicts climatic variables and optimizes green roof performance based on sensor inputs. Model parameters are iteratively updated to minimize the error between predicted and actual conditions, while hyperparameter tuning further enhances performance. After training, the model is validated using a separate dataset to assess generalization capability and avoid overfitting. If necessary, the architecture or hyperparameters are refined to improve results. After validation, the trained model is tested on an independent dataset to evaluate its accuracy, robustness, and computational efficiency. The final model is then integrated with IoT-enabled green roof systems, enabling real-time operation. In this phase, the trained RNN is deployed on a platform that continuously receives sensor data, generates predictions, and triggers automated actions—such as adjusting irrigation, ventilation, or shading systems to optimize performance. Collaboration among data scientists, domain experts, and engineers ensures seamless integration with IoT devices. The final stage involves full-scale deployment of the RNN-integrated IoT system in urban environments. Continuous monitoring and stakeholder feedback help refine system accuracy and adaptability. Regular maintenance and updates are performed to ensure long-term functionality and sustainability. This iterative cycle ensures that IoT-enabled green roof systems dynamically regulate environmental conditions, thereby mitigating UHIs, conserving resources, and promoting biodiversity.

Green Roof Sensors

To optimize performance and sustainability, the proposed IoT-enabled smart green roof system incorporates a network of sensors strategically positioned across the roof structure. These sensors continuously monitor key environmental parameters, ensuring ideal conditions for plant growth, water management, and energy efficiency.

1. **Temperature Sensors** – Measure ambient and surface temperature to support thermal regulation, improve energy efficiency of buildings, and maintain plant vitality.
2. **Humidity Sensors** – Track atmospheric moisture levels, which are essential for plant transpiration, growth, and microclimate regulation.
3. **Soil Moisture Sensors** – Monitor soil water content, enabling precise irrigation scheduling and minimizing excess water consumption.
4. **Air Quality Sensors** – Detect pollutants such as CO_2, volatile organic compounds (VOCs), and particulate matter to evaluate environmental quality and plant health.
5. **Light Intensity Sensors** – Measure solar radiation levels to optimize plant photosynthesis, regulate shading, and enhance overall vegetation development.
6. **Soil pH Sensors** – Continuously assess soil acidity or alkalinity, ensuring balanced nutrient availability and healthy plant growth conditions.

Figure 1 illustrates the block diagram of the proposed system, showing the flow of data and operations from sensor acquisition → preprocessing → RNN-based prediction → IoT actuation → feedback loop, enabling efficient and adaptive green roof management.

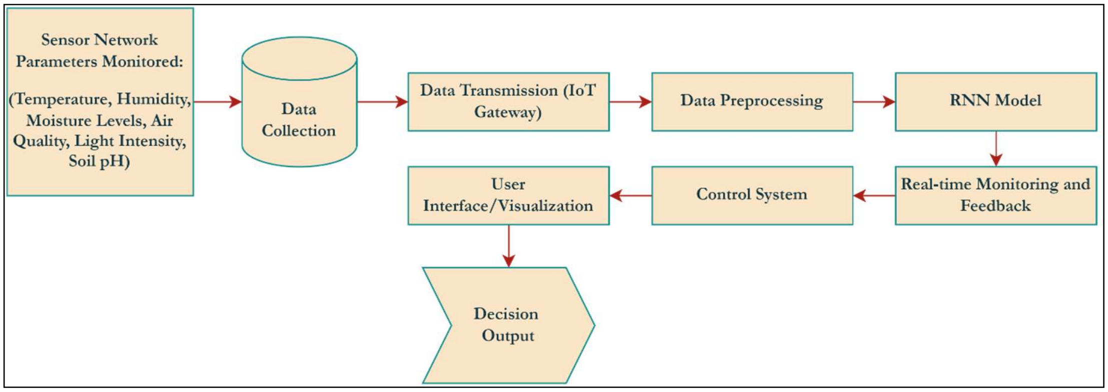

FIGURE 1. Block diagram of Proposed IoT-Driven Green Roof Management with RNN

By incorporating these sensors into an IoT-enabled smart green roof system, environmental parameters can be comprehensively monitored and optimized in real time. This intelligent system is designed not only to support plant health but also to mitigate the urban heat island effect, improve air quality, and foster urban biodiversity. Leveraging live sensor data, the system adaptively adjusts irrigation, ventilation, and energy use, thereby enhancing the overall efficiency and resilience of green roofs. Through continuous monitoring and adaptive control, the smart green roof contributes significantly to urban sustainability, climate resilience, and ecological balance. The sensor network plays a crucial role in managing and supporting decision-making within urban green roof ecosystems. By continuously monitoring environmental parameters, analyzing real-time data, and providing automated feedback, the system enhances adaptive management strategies. This capability contributes to creating more resilient, sustainable, and livable cities. To enable dynamic environmental management, the collected sensor data is processed through a Recurrent Neural Network (RNN) model. This model learns from temporal patterns in the data, enabling accurate predictions and proactive system responses. Table 1 outlines the data flow within the RNN process, illustrating how raw sensor inputs are transformed into actionable insights for optimizing the performance of the green roof system.

TABLE I. Sensor Reading and Pollution Levels System Workflow

Step	Description
Data Input	Time-series environmental data (temperature, humidity, moisture, light, etc.) from sensors.
Data Preprocessing	Clean and normalize data, handle missing values, and transform data for RNN input.
Sequence Modeling	RNN processes sequential data, capturing temporal dependencies and patterns.
Prediction Output	RNN generates predictions for future environmental conditions (temperature, humidity, etc.).
Decision Making	Predictions are compared with thresholds to trigger adjustments in the system.
Control Action	Automated systems (e.g., irrigation, shading) adjust based on RNN predictions.
Model Training	Periodically retrain the RNN with updated data to improve prediction accuracy.

RESULTS AND DISCUSSIONS

The integration of IoT-enabled sensors with Recurrent Neural Networks (RNNs) significantly enhances environmental regulation, sustainability, and overall efficacy in smart green roof systems. The sensor network, comprising temperature, humidity, soil moisture, light intensity, air quality, and soil pH sensors collected real-time data continuously over several weeks. This data provided critical insights into the dynamic behaviour of the green roof, capturing variations in environmental parameters throughout the day and under different weather conditions. Through IoT connectivity, the system enabled autonomous, latency-free monitoring, ensuring reliable and extensive data collection. The time-series data was processed and used to train an RNN model, which forecasted future environmental variables such as temperature, soil moisture, and humidity. The model was then evaluated for its predictive reliability. Preliminary results showed a strong correlation between predicted and observed values, achieving an average prediction error below 5% for temperature, humidity, and soil moisture. This level of precision demonstrated the model's ability to capture complex temporal patterns and deliver dependable forecasts for adaptive green roof management.

The predictive capability of the RNN facilitated proactive decision-making. For example, predicted soil moisture levels allowed the system to adjust irrigation schedules dynamically, preventing both overwatering and underwatering. Similarly, forecasts of temperature and humidity enabled optimization of shading and ventilation systems, thereby improving plant health while minimizing energy use. A key advantage of the system was resource optimization: by aligning irrigation with predicted rainfall and soil conditions, water consumption was reduced by up to 20% compared to traditional fixed schedules. Likewise, temperature-based adjustments to cooling systems reduced energy demand while maintaining optimal plant growth conditions. Overall, the system demonstrated notable improvements in green roof management, including enhanced plant vitality, increased energy efficiency, and improved occupant comfort within the building. Moreover, the predictive analytics framework provided faster response times to environmental challenges, allowing the system to adjust before conditions reached a critical threshold.

However, the trial also highlighted several challenges. Sensor calibration and maintenance proved essential, as gradual deviations in sensor readings required periodic recalibration to preserve accuracy. External influences such as sudden weather fluctuations or occasional sensor failures sometimes led to discrepancies between predicted and observed outcomes. These issues emphasized the importance of implementing robust fault detection and system recovery mechanisms. Furthermore, while the RNN achieved strong predictive performance, its training process demanded substantial computational resources and time, which posed scalability challenges. To address these factors, the system's training framework was designed to capture diverse time-series datasets across environmental parameters. Table 2 illustrates the RNN training process, highlighting how input data such as soil pH, temperature, and humidity were processed to improve predictive performance and ensure reliable decision support for green roof management.

TABLE 2. Time-Series Data for RNN Model

Time (Day/Time)	Temperature (°C)	Humidity (%)	Soil Moisture (%)	Light Intensity (Lux)	Air Quality (CO2 ppm)	Soil pH
2024-12-01 06:00	15.2	80	45	320	400	6.5
2024-12-01 12:00	18.3	70	50	800	380	6.6
2024-12-01 18:00	16.7	75	48	600	390	6.6
2024-12-02 06:00	14.8	82	47	310	410	6.5
2024-12-02 12:00	19.2	68	52	850	370	6.6
2024-12-02 18:00	17.5	73	49	620	395	6.5
2024-12-03 06:00	15.0	80	46	330	400	6.4

Figure 2 illustrates the predicted trends of temperature and soil moisture generated by the RNN model over time. These forecasts support dynamic decision-making in IoT-enabled green roof management systems by enabling timely adjustments to irrigation, shading, and ventilation strategies, thereby ensuring optimal plant growth and resource efficiency.

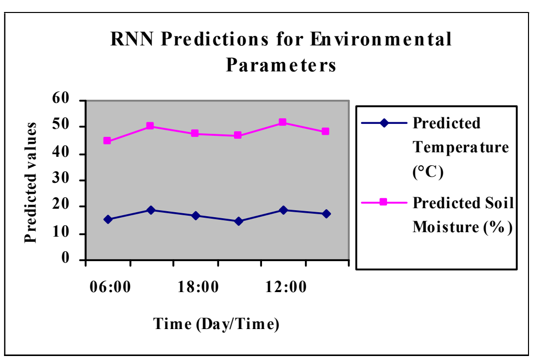

FIGURE 2. Time-Series Prediction Graph for Green Roof Management

Figure 3 illustrates the decline in training loss across multiple epochs. This downward trend indicates that the RNN model is progressively assimilating patterns from the input data, thereby enhancing its predictive capability and ensuring improved accuracy in green roof environmental forecasting.

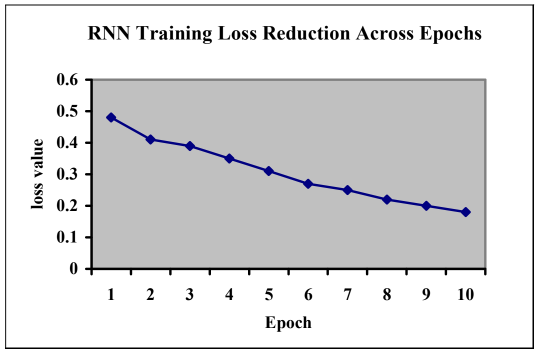

FIGURE 3. RNN Epoch-wise Loss Curve

Figure 4 shows the training accuracy across epochs, demonstrating a steady improvement as the RNN model progresses. The rising accuracy indicates superior learning performance and enhances predictive capability.

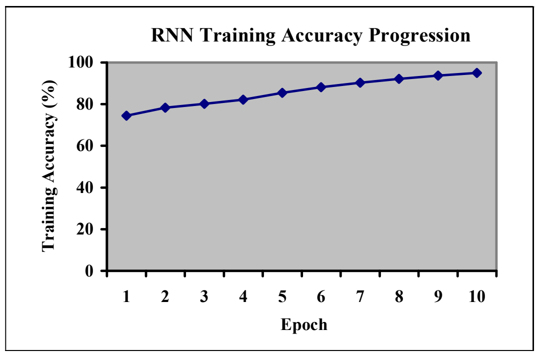

FIGURE 4. RNN Training Accuracy Improvement Across Epochs

Table 3 presents the dataset sizes used in the training, validation, and testing phases of the RNN model. Each subset was allocated appropriately to ensure balanced evaluation and reliable assessment of the model's performance.

TABLE 3. Dataset Distribution for RNN Model Training

Dataset Name	Train Size	Validation Size	Validation Size
Temperature Data	4000	500	500
Soil Data	4800	600	600
Sensor Data	8000	1000	1000
RNN Training Data	6000	750	750

Table 4 compares the performance of the RNN model with alternative approaches, including LSTM, GRU, Random Forest, and SVM, based on key evaluation metrics.

TABLE 4. Comparison of RNN and Other Models

Model	Accuracy (%)	Precision	Recall	F1 Score
RNN	92.5	90.3	91.2	90.7
LSTM	89.4	87.5	88.3	87.9
GRU	88.2	85.7	86.9	86.3
Random Forest	84.6	81.9	82.7	82.3
SVM	80.5	77.2	78.1	77.6

As the system accumulates larger datasets, the RNN model requires frequent retraining, which can be resource intensive. Future versions of the system may explore more efficient machine learning architectures or optimization strategies to reduce training duration and computational demands. The demonstrated efficacy of this IoT-enabled green roof management framework paves the way for further advancements in intelligent urban agriculture and sustainable construction practices. Future research could incorporate additional sensing modalities, such as wind speed and solar radiation sensors, to improve the precision of environmental monitoring and control. Moreover, integrating hybrid approaches that combine RNNs with reinforcement learning or ensemble methods may enhance both predictive accuracy and adaptive decision-making. Scaling the system to support larger and more complex green roof installations would also provide valuable insights into its scalability and operational flexibility. Cloud computing integration offers another promising direction, enabling enhanced data storage, faster model training, and real-time decision support, thereby facilitating large-scale deployment in urban environments.

The findings further demonstrate that the system contributes to urban biodiversity and ecological resilience. Green roofs act as habitats for diverse plant species, insects, and birds, delivering crucial ecosystem services within cities. By combining IoT-based monitoring with RNN-driven predictive analytics, the system not only optimizes resource use but also fosters conditions conducive to local flora and fauna. For instance, the predictive framework can identify microclimatic conditions favorable to specific plant species or pollinators, supporting long-term ecosystem health and protection. Overall, the results indicate that the proposed approach is both scalable and transferable. Although the study focuses on a hypothetical urban environment, the methodologies and insights are broadly applicable to real-world metropolitan contexts worldwide, contributing to smarter, greener, and more sustainable cities.

CONCLUSIONS

RNN models within IoT-enabled green roof management systems are transforming urban environmental management. This innovative framework integrates advanced predictive analytics with ecological principles, offering effective strategies for mitigating the urban heat island effect while enhancing biodiversity. By leveraging temporal dependencies in sequential data, RNN models accurately forecast environmental conditions from IoT sensor inputs, enabling real-time monitoring and adaptive optimization of green roof operations. The proposed approach provides distinct advantages. First, it improves the accuracy and efficiency of environmental regulation by optimizing key parameters such as temperature, soil moisture, and plant health. Second, it strengthens urban ecosystems and public well-being by supporting biodiversity and ecosystem services. Importantly, RNN-based frameworks are both scalable and versatile, making them suitable for diverse metropolitan contexts from dense megacities to smaller urban centers while remaining adaptable to local conditions and sustainability priorities. Overall, RNN-driven IoT green roof systems represent a significant step toward more resilient and livable urban landscapes. Through data-driven decision-making and adaptive environmental control, cities can harness green infrastructure to counteract the adverse impacts of urbanization and foster healthier, more sustainable ecosystems for future generations.

REFERENCES

[1]. S. Y. Saleh, and O. G. Alfarra, 2023, "The effect of green roofs-types on the design of energy-efficient buildings in Gaza strip: A co-simulation parametric study," *8th International Engineering Conference on Renewable Energy & Sustainability*, pp. 1-5.

[2]. A. Gandini, D. Navarro, and E. Feliu, 2023, "Identification and mapping of areas and buildings with high roof greening potential," *Joint Urban Remote Sensing Event*, pp. 1-4.

[3]. N. Stamler, 2023, "City-scale analysis of green roof effectiveness in reducing local surface temperatures," *IEEE International Geoscience and Remote Sensing Symposium*, pp. 3604-3609.

[4]. M. V. Bueno de Morais, V. V. U. Guerrero, L. D. Martins, and E. R. Marciotto, 2023, "A mesoscale modeling analysis of green roof impact in the thermal field in the Mediterranean Chilean urban areas," *IEEE International Smart Cities Conference*, pp. 01-05.

[5]. K. L. Rao, 2023, "Performance upgradation of roof top solar PV systems for establishing green electricity," *2nd International Conference on Futuristic Technologies*, pp. 1-5.

[6]. M. Gholamnia, P. Sajadi, S. Khan, S. Sannigrahi, S. Ghaffarian, and H. Shahabi, 2024, "Assessment and modeling of green roof system hydrological effectiveness in runoff control: A case study in Dublin," *IEEE Access*, 12, pp. 189689-189709.

[7]. T. Husting, B. Schröder, and S. Weber, 2024, "Predicting multi-annual green roof net ecosystem exchange using machine learning," *Building and Environment*, 263, Article. 111878.

[8]. M. A. Rahman, D. Stone, A. Rahman, and M. A. Alim, 2024, "Towards adaptive green infrastructure:

Artificial intelligence and machine learning-based modelling for green roofs," *Proceedings of Hydrology and Water Resources Symposium*, pp. 273–282.

[9]. C. Wang, J. Guo, and J. Liu, 2024, "Green roofs and their effect on architectural design and urban ecology using deep learning approaches," *Soft Computing*, 28 (4), pp. 3667–3682.

[10]. F. Rahmaniah, and S. E. Rong Tay, 2024, "Comparison of photovoltaic green roofs and agricultural photovoltaics across climate zones – benefits and recommendations," *IEEE 52nd Photovoltaic Specialist Conference*, pp. 1-3.

[11]. R. Veer Samara Sihman, M. M. Almusawi, M. Hussein Fallah, T. Saravanan, and N. Rajesh, 2024, "Green roof optimization using multi objective optimization with genetic programming based artificial neural network," *International Conference on Integrated Intelligence and Communication Systems*, pp. 01-05.

[12]. S. Mousavi, M. Gheibi, S. Wacławek, and K. Behzadian, 2023, "A novel smart framework for optimal design of green roofs in buildings conforming with energy conservation and thermal comfort," *Energy and Buildings*, 291, Article. 113111.

[13]. A. Goldschmidt, and I. Buffam, 2023, "Biochar-amended substrate improves nutrient retention in green roof plots," *Nature-Based Solutions*, 3, Article. 100066.

[14]. Y. Nasr, H. El Zakhem, A. E. A. Hamami, M. El Bachawati, and R. Belarbi, 2024, "Comprehensive assessment of the impact of green roofs and walls on building energy performance: a scientific review," *Energies*, 17 (20), Article. 5160.

[15]. M. Shehzad, A. Younis, M. Asif, and M. Hameed, 2023, "Prospects of green roof technology as a sustainable solution to urban pollution index," *Journal of Agriculture and Food Research*, 14, Article. 100751.

[16]. E. M. H. Abdalla, K. Alfredsen, and T. M. Muthanna, 2023, "On the use of multi-objective optimization for multi-site calibration of extensive green roofs," *Journal of Environmental Management*, 326, Article. 116716.

[17]. L. Lai, J. Wang, F. Li, E. Zou, W. Yang, and Y. Zhang, 2025, "Thermal performance prediction of rainwater-vented composite green roofs using the VMD-TCN-GRU model," *Journal of Building Engineering*, 103, Article. 112152.

[18]. D. Gößner, M. Kunle, and M. Mohri, 2025, "Green roof performance monitoring: Insights on physical properties of 4 extensive green roof types after 2 years of microclimatic measurements," *Building and Environment*, 269, Article. 112356.

[19]. A. A. Kafy, 2024, "Integrating 2D-3D urban morphological characteristics in predicting green roof cooling potential for mitigating diurnal surface urban heat island intensity," Doctoral dissertation.

[20]. M. Villacis-Ormaza, 2025, "An experimental study on the thermal performance of intensive green walls and green roofs in temperate continental climatic zones," *Future Cities and Environment*, 11(21), pp. 1-21.