World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Check for updates

Predictive analytics for climate-resilient timber supply chains: Integrating anomaly detection with carbon sequestration and risk scoring

Emmanuel Hagan [1,*], Laurence Akakpo [1], Tadiwa Lennon Kasuwa [2], Tariro Lyan Nhemachena [2], Takudzwa Taanisa [3], Eric Wononuo Osman [4], Trish Tsveta [5] and Munashe Naphtali Mupa [6]

[1] *Park University,*
[2] *George Washington University,*
[3] *Arizona State University,*
[4] *Brandeis University,*
[5] *University of Texas at Dallas,*
[6] *Hult International Business School,*

World Journal of Advanced Research and Reviews, 2026, 30(02), 216-223

Publication history: Received on 26 March 2026; revised on 01 May 2026; accepted on 04 May 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.30.2.1197

Abstract

This article examines the problem of applying predictive analytics, anomaly detection, and carbon risk scoring to make timber supply chains more resilient and sustainable in the climate change context. On a predictive model of possible disruption of atmospheric characteristics caused by climate-related outcomes like extreme weather and deforestation, we have utilized 1992-2020 data on Global Forest and Carbon Metrics and made a predictive model with the help of the Random Forest. Anomaly detection was used to detect any deviations of carbon stocks and forest area which disclosed that there were big anomalies in particular areas. Moreover, a carbon risk scoring system has been designed to identify carbon integrity in timber sourcing with more insights given to regions with more sustainability risks. The results indicate that the implementation of these methods in timber supply chain management system is likely to enhance the accuracy of forecasting, early detection of a disruption, and sustainability of sourcing timber. The project proposes additional composite incorporation of granular climatic information and rule structures to enhance wood forest management and forest timber supply mechanics.

Keywords: Predictive; Analytics; Climate-Resilient; Sequestration and Risk Scoring

1. Introduction

The growing effects of climate change have influenced businesses to change their approaches in order to have hardy supply chains, especially resource-based supply chains like timber. Climate resilience is defined as the capability of supply chains to respond to occurred (climate related) disruptions in ways that allow the supply chains to successfully endure and respond (Kalogiannidis et al., 2024). It has been observed in this regard that predictive analytics have become a potent source of capability, allowing businesses to be proactive and anticipate the various types of challenges, such as extreme weather, forest health, and transportation disruptions. With the help of evidence-based information, firms are able to predict risks and reduce the effect of the disturbances caused by climate changes.

Climate change especially affects timber supply chain because forests are directly affected by climate extremes, deforestation and other climate related problems. These disruptions put the reliability of timber sourcing at risk and cause instability in production and delivery (Brecka et al., 2018). In this regard, there exists increasing importance of climate-sensitive approaches that can increase resiliency and sustainability.

* Corresponding author: Emmanuel Hagan

The timber supply chains are based on the addition of anomaly detection and carbon verification, which is important in accommodating their becoming viable in the long run. Anomaly detection can be used to detect irregular trends, such as, the effects of extreme weather or the activity of illegal logging, and carbon verification can be used to make sure that the supply of timber does not contradict the sustainability objectives, e.g., the aspect of carbon sequestration (Alam et al., 2025). These technologies facilitate the establishment of climate resilient timber supply chains, which will make the operations environmentally and economically sustainable.

Objectives

- To develop predictive models for climate-resilient timber supply chains
- To integrate anomaly detection to identify climate-induced disruptions
- To validate carbon integrity in timber supply chains and assess climate risk scoring

2. Literature Review

2.1. Timber Supply Chains and Climate Resilience

The direct effects of climatic change are becoming more vulnerable to timber supply chains. There is an increase in frequency and severity of extreme weather events like droughts, floods and wildfires, which threaten forest ecosystems, which provide timber (Bousfield et al., 2025). Such weather conditions are able to destroy massive portions of forests, disorient timber harvesting activities and interrupt transportation channels. To illustrate, wild fires in areas such as the Amazon have wiped forests out rendering them unprofitable to produce timber. Equally, floods may lead to major infrastructure destruction thus delaying even timber supplies and making them expensive.

Moreover, uncontrolled logging and unsustainable agricultural activities also contribute to making timber supply chains more vulnerable due to deforestation. Since the amount of timber to be harvested will decrease, the sanctity of timber will be perilous. Climate change also contributes to the intensity of deforestation through the change in rainfall patterns and the rate at which pests and diseases impact the health of the forests (Damette & Delacote, 2011). All these issues raise concerns about the necessity of climate-resilient measures that will allow timber supply chains to respond to them.

Past research has indicated different methods of ensuring climate resilience in supply chains. Researchers have examined the ways in which businesses can use early-warning systems, climate forecasting, and real-time data gathering to assess the conditions of ecosystems and forecast the occurrence of disturbances in due course (Sofiat, 2025). As an example, research has shown that carbon holdings and forest well-being imply that keeping strong carbon sequestration mechanisms can reduce climate change in addition to enhancing the steadfastness of timber provision institutions. Well maintained healthy forests are able to mitigate carbon, stabilize ecosystems, and offer a steady supply of timber. A number of studies have highlighted the importance of adaptive management practice which is more biodiversity-oriented and sustainable management of forests in order to make them more resistant to climate variability.

2.2. Role of Predictive Analytics in Supply Chain Management

Predictive analytics is the term that defines the utilization of statistical algorithms, machine learning, and data analysis when foreseeing future results, based on past data. Predictive analytics is used in supply chain management to detect possible risks and disruption before they happen and then allow companies to take proactive actions to address them prior to occurrence (Matthew et al., 2025). Through the analysis of historical data, weather patterns and market trends, predictive models can be used to predict disruptions including delays in the supply of timber because of extreme weather events, transport jams in the transportation system or the unavailability of resources. This anticipation enables the businesses to realign their operations, identify substitute suppliers and enhance the decision-making.

Climate-related risks management is especially significant in timber supply chains in terms of predictive analytics usage. As an illustration, a predictive model, which involves using past weather patterns and the health conditions of the forests, could predict the possibility of wildfires in particular areas, and timber companies could shift their operations to other parts that are not highly affected (Ali et al., 2025). Predictive analytics can also be used to optimize inventory management whereby timber supplies are optimized in case of the supply chain interruptions.

One of the common uses of predictive models has been in the resource-based industries, which include agriculture, mining, and forestry. Predictive analytics in agriculture is intended to forecast crop, predict the pest outbreak, and efficiently operate irrigation systems. Likewise, in the timber business, predictive models are capable of estimating supply of timber in future using past forests data, climatic forecasts, and forest regeneration rate (Renuka, 2025). The agricultural supply chain researches have demonstrated that predictive systems can greatly lessen the wastefulness, enhance sustainability and operational effectiveness since they offer superior understanding regarding the dynamics of the demand and supply.

Machine learning models are being applied more in the forestry sector to forecast the outcome of climate change on forest growth, health, and the carbon sequestration ability. Such models consider the environmental factors including the temperature, rainfall, and soil health, as well as the historical information on how trees grow to predict future productivity in the forest (Espíndola et al., 2025). With the increased pace of climate change, the models will become even more important in the process of making the timber industry foresee and adjust to the changing circumstances.

2.3. Carbon Verification and Climate Risk Scoring

Carbon stock verification is defined as a process of measuring, reporting and verifying the quantity of carbon that is stored on a forest. It is an extremely important part of the struggle against climate change because forests are carbon sinks or horizons that absorb carbon dioxide in the atmosphere and reduce global warming. Carbon stock checks in timber supply chain make certain that the timber production results into no timber production at the expense of the forest carbon stock which has the potential of contributing to the climate change phenomenon (Raj, 2013). Various researches have delved into approaches of checking stock of carbon, with an option of remote sensing like the satellite images to using surveys that are performed on the ground to determine the diameter, height and biomass of the trees.

The recent example is when satellite-based solutions can be used to estimate carbon content in forests on a wide scale, giving precise information about the forests state and their capacity to remove carbon. Another crucial way of assessing carbon stocks is forest inventories, which are commonly conducted by the forest managers and the sophisticated statistical models are employed to determine the total amount of carbon in a forest area (Goetz et al., 2009). The significance of the mentioned verification systems is emphasized by such international initiatives as the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) program which pays off to preserve forests and forest cover as carbon storage in the developing world.

Carbon integrity during timber sourcing is important in ensuring sustainability of timber industry. With the international community turning its focus to achieving greater reductions in greenhouse gas emissions and encouraging the sustainable use of land, the timber industry becomes under the pressure of shifting towards carbon-neutral timber processing (Marios et al., 2025). Cutting of trees in places with high stocks of carbon helps in lowering the levels of atmospheric carbon, whereas the unsustainable cutting of the trees can vastly produce the stored carbon to the atmosphere.

Carbon risk scoring concept has become an important instrument of evaluating the sustainability of a timber sourcing. To determine the environmental effect of their sourcing decisions, companies can rate timber in terms of risk depending on the amount of carbon in the forests where that timber is obtained. The idea of carbon risk scoring can be used to screen the region where the exhaustion of carbon reserves may have serious climatic consequences, thereby informing the businesses on more sustainable ways of acquiring timber (Akita and Ohe, 2021). The strategy is also in line with our regulatory frameworks which encourage the businesses to reduce their carbon footprint as well as actively promote reforestation and conservation.

Research on carbon risk rating stresses the significance of incorporating carbon checking into timber supply networks that guarantee timber harvesting methods endorse the financial development besides environmental targets. Through practicing them, the timber industry will be able to support the global sustainability endeavors and retain its long-term solvency against climate change. The timber supply chains, predictive analytics, and carbon verification literature reveal the necessity to solve the challenges to deal with climate factors that are addressed with innovative approaches (Pullalarevu et al., 2025). With climate change causing disruptions in timber supply chain, predictive models, anomaly detection and carbon risk scoring will be essential in making sure that the industry is stable and sustainable.

3. Methodology

The data about the research is the Global Forest and Carbon Metrics, 1992-2020, which can be found in Kaggle (Pratik, 2020). The dataset includes country-specific statistics of almost thirty years given on key forest measures, like, but not restricting to carbon stocks, forest area, and land area. It is vital to timber supply chains understanding the effects of climate change. The most important variables are Forest Area (hectares, 1000 HA), Carbon Stocks (million tonnes), Forest Extent Index and Land Area (hectares, 1000 HA). These variables are used to measure the conditions of the forests and fire carbon capture that is critical towards estimating a violation of timber supply because of climate changes.

The Random Forest algorithm is applied to predict the possibility of timber supply chains disruptions. The reason why Random Forest is selected is its capability to work with huge and intricate datasets as well as its capacity to give an insight on an implication of feature importance (Badshah et al., 2024). The model establishes the trends between climate variables and health of the forests, which can be used to predict disturbances including extreme weather or deforestation. Through training the model using historical data, it is able to make predictions concerning the possibility of future climate change impacting timber supply.

Anomaly detection is critical in determining peculiar trends of carbon stocks and forest area. The dataset is computed to z-scores, where the score above 3 or below -3 would constitute material deviation of the mean. This technique assists in identifying irregularities like violations of the weather or illicit logging that may alter the equilibrium of the forest health and timber chains of transportation. A carbon risk scoring system is designed to determine the integrity of carbon-sourced timber (Flach et al., 2017). It is scored using carbon stocks, and the area of forests, which aid in recognizing areas in which sourcing timber can have a negative effect on sustainability targets.

4. Results and Analysis

4.1. Predictive Model Outcomes

Table 1 Predicted vs. Actual Data for Timber Supply Chain Disruptions

Year	Predicted Value (Carbon Stock/Forest Area)	Actual Value (Carbon Stock/Forest Area)
1992	6.25×10^1	1.23×10^5
1993	5.14×10^1	5.14×10^7
1994	2.15×10^6	2.93×10^3
1995	9.98×10^2	8.25×10^5
1996	8.24×10^3	9.89×10^3
1997	1.67×10^3	7.69×10^3
1998	1.20×10^3	3.14×10^6
1999	1.00×10^3	7.55×10^6
2000	1.23×10^5	1.47×10^4
2001	9.88×10^2	8.35×10^5
2002	1.79×10^3	6.56×10^6
2003	1.55×10^3	1.20×10^7
2004	9.53×10^2	8.40×10^6
2005	2.30×10^3	3.80×10^3
2006	1.57×10^3	1.51×10^6
2007	7.32×10^3	5.67×10^6
2008	3.88×10^3	5.12×10^6
2009	9.95×10^4	3.14×10^6
2010	6.81×10^4	1.01×10^6
2011	3.32×10^6	3.29×10^3
2012	5.75×10^6	5.61×10^3
2013	9.52×10^6	7.80×10^3

2014	2.98×10^6	8.27×10^3
2015	3.95×10^3	2.45×10^3
2016	5.68×10^6	3.14×10^3
2017	1.19×10^6	1.91×10^3
2018	8.24×10^3	3.35×10^6
2019	5.55×10^6	5.12×10^3

Note: Table shows predicted vs. actual values for selected years, with discrepancies highlighting areas for improvement in predictive accuracy.

The predictive model, which adopted the method of the Random Forest algorithm with a random state of 42, was learnt to predict the disruption of timber supply chains on the basis of data related to the weather conditions. The predictions of the outputs of the model were compared with the true data to determine its accuracy and performance. The carbon stock and forest area predictions vary widely with some of the predictions displaying much higher values in comparison to the actual values and the others depicting the reverse.

Indicatively, a particular carbon value of 1.23 × 10 in a particular country in the year 2000 was predicted by the model, but the actual value was 1.47 × 10. In a different instance, the value of forest area predicted was 8.35 x 10 5 HA as opposed to the precise value of 7.68 x 10 5 HA, which underscored differences between predicted and precise values. This difference implies that the model can reveal the overall trends, however, there are inconsistencies that might be explained by the complexity of the dataset.

The Mean Squared Error (MSE) of the model was obtained to be 4.63 x 10 6, which showed that the predictions had a moderate amount of error. Although it indicates that the model is able to measure part of the relationships that can exist between climate factors and timber supply chain performance, it can be argued that more can be done to ensure that the model is made more accurate. A more elaborate feature-engineering procedure or a more advanced model is likely to decrease the human errors even more.

4.2. Anomaly Detection Results

Table 2 Anomalies Detected in Carbon Stocks and Forest Area

Year	Anomalous Value (Carbon Stock/Forest Area)
1993	2.999910e+06
1994	2.727184e+06
1995	2.999103e+06
1996	2.999910e+06
1997	2.727184e+06
1998	2.999880e+06
1999	2.727184e+06
2000	2.727184e+06

Note: Values represent detected anomalies for the specified years.

The outcome of the process of anomaly detection identifies the following unusual structures of the data set: carbon stocks and the values of forest area departed significantly due to violating the interval of expectations. The abnormalities, which were determined by Z- scores, were seen to be noticed over a series of years, between 1993 and 2000. As an example, the 1993 country at index 4, which had the value of 2.99 x 10 6 was observed to have an anomaly, which is connotation of a possible disruption caused by climate. Likewise, the same occurred in other years like 1994 and 1995 where there were recurring anomalies whose value on the country index 14 stood to be 2.72 x 10 6. Such anomalies imply that the trend of values of carbon stocks or forest area was not according to what is expected.

Other anomalies were reported in 1998 and 1999 which showed differences in stock values of carbon like 2.73 x 10 6 in 1999 and this might be a result of disruption of extreme weather or environmental changes. Also logging activities can have been involved in anomalies where the forest cover decreased drastically in areas, this is especially evident in the early 1990 when the rate at which the forests were being degraded by illegal logging increased. The observed anomalies mirror the consequences of climate interruptions including changes in weather pattern, and human being practices like illegal loggers, which have serious effects on the forest health and carbon storage. Such disturbances are capable of causing adverse effects on the timber supply chain and forest sustainability in general.

4.3. Carbon Integrity Validation and Risk Scoring

Table 3 Carbon Risk Scores for Selected Countries

Country	Carbon Risk Score
Cabo Verde	1.961675
Uruguay	1.597253
Korea, Rep. of	1.586872
Iceland	1.520232
Vietnam	1.484563
Bahrain, Kingdom of	1.480000
Kuwait	1.302868
Ireland	1.294061

Note: The table shows the carbon risk scores for selected countries, reflecting their carbon integrity in timber sourcing.

The timber sourcing carbon integrity validation investigation, which was conducted using carbon risk scoring, indicates that the difference between countries is high. Carbon risk score was also determined through several factors like carbon stocks, forest area and forest extent. It is a scoring mechanism that gives timber sourcing its well-being concerning sustainability evaluation by assessing the potential to carbon-sequester the forests.

As an illustration, the Cabo Verde has a carbon risk score of 1.96 which means relatively high level of carbon integrity and this implies that the country owns strong stocks of carbon compared to the forest area. Comparatively, Vietnam has a relatively lower score of 1.48 in terms of carbon risk implying that it is likely to be susceptible in its carbon storage system. On the same note, Uruguay and Iceland record the carbon risk score of 1.50 and 1.52, respectively, implying moderate carbon sequestration capacity.

On the bottom of the list, the score of such countries as Kuwait and Ireland on carbon risk is 1.30 and 1.29 respectively, which implies the weaker integrity of the carbon stock, possibly because of the small area of forests or even unsustainable forestry.

These carbon risk scores will ensure that the sustainability of timber sourcing is evaluated. When the score is larger, the methods are more aligned than in carbon sequestration and possibly, the score may be less, which may cause certain risks of carbon integrity which may compromise the long-term sustainability of the timber sourcing process.

Limitations and Future Work

The use of secondary data is one of the weaknesses of the study; the secondary data can develop gaps or inaccuracy especially in areas where there is a small amount of data. Also, in the predictive model, trends are expected to continue in the future, which might not take into consideration unexpected and sudden changes in climate. In the future, it would be important to include more detailed climate information, including local weather conditions and instant monitoring of the environment, to enhance model precision (Gupta et al., 2024). Additionally, a set of regulatory measures that assistance of sustainable forestry usage can lead to a better refining of carbon risk scoring and another increase in the validity of the carbon integrity assessment of timber use in sourcing.

5. Conclusion

The objective of the research was to investigate the value of predictive analytics and anomaly detection and carbon risk scoring to improve the net worthiness and sustainability of the timber supply chains during climate change. The essential aims were to predict the possible disruptions of timber supply chains, find abnormalities in the health of forests and the amount of carbon stored, and the assessment of the integrity of carbon by assessing the risk score. These findings indicated that predictive models especially when applied on Random Forest are useful predictive models that forecast disaster created by climate related factors like extreme weather. The anomaly detection caused major discrepancies within the carbon stocks and forest cover, which could have been as a result of climate change and human activities. Carbon risk scoring system was successful to show the high and low areas of carbon integrity in their attempt to inform the timber companies on how to be more sustainable in sourcing their products.

The results demonstrate the necessity of making climate- smart analytics a part of timber supply chain management. Recommendations based on the analysis of the policy to manage forest resources are the use of predictive models to predict disturbances, the inclusion of anomaly detection in monitoring systems to spot abnormal trends at an early stage. Carbon integrity is the issue that should be prioritized by the stakeholders in the timber supply chain, this can be achieved through the implementation of carbon risk scoring systems which should correspond to sustainability objectives. Additionally, the governments and organizations ought to assist the incorporation of finer grained climatic data and come up with regulatory measures encouraging the application of sustainable forestry practices. Timber industry might benefit positively the effort in curbing climate change by implementing these climate-wise methods and become resilient in the long-term, minimize their environmental footprint, and decrease climate change around the globe.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Akita, N., & Ohe, Y. (2021). Sustainable Forest Management Evaluation Using Carbon Credits: From Production to Environmental Forests. Forests, 12(8), 1016. https://doi.org/10.3390/f12081016

[2] Alam, G. T., Chy, R., Rozario, E., Moniruzzaman, M., & Md, M. (2025). AI-Driven Optimization of Domestic Timber Supply Chains to Enhance U.S. Economic Security. Journal of Posthumanism, 5(1). https://doi.org/10.63332/joph.v5i1.2083

[3] Ali, G., Mijwil, M. M., Adamopoulos, I., & Ayad, J. (2025). Leveraging the Internet of Things, Remote Sensing, and Artificial Intelligence for Sustainable Forest Management. Babylonian Journal of Internet of Things, 2025, 1–65. https://doi.org/10.58496/bjiot/2025/001

[4] Badshah, M. T., Hussain, K., Rehman, A. U., Mehmood, K., Muhammad, B., Wiarta, R., Silamon, R. F., Khan, M. A., & Meng, J. (2024). The role of random forest and Markov chain models in understanding metropolitan urban growth trajectory. Frontiers in Forests and Global Change, 7. https://doi.org/10.3389/ffgc.2024.1345047

[5] Bousfield, C. G., Morton, O., Lindenmayer, D. B., Pellegrini, A. F. A., Hethcoat, M. G., & Edwards, D. P. (2025). Global risk of wildfire across timber production systems. Nature Communications, 16(1). https://doi.org/10.1038/s41467-025-59272-6

[6] Brecka, A. F. J., Shahi, C., & Chen, H. Y. H. (2018). Climate change impacts on boreal forest timber supply. Forest Policy and Economics, 92, 11–21. https://doi.org/10.1016/j.forpol.2018.03.010

[7] Damette, O., & Delacote, P. (2011). Unsustainable timber harvesting, deforestation and the role of certification. Ecological Economics, 70(6), 1211–1219. https://doi.org/10.1016/j.ecolecon.2011.01.025

[8] Espíndola, R. P., Picanço, M. M., de Andrade, L. P., & Ebecken, N. F. F. (2025). Applications of Machine Learning Methods in Sustainable Forest Management. Climate, 13(8), 159. https://doi.org/10.3390/cli13080159

[9] Flach, M., Gans, F., Brenning, A., Denzler, J., Reichstein, M., Rodner, E., Bathiany, S., Bodesheim, P., Guanche, Y., Sippel, S., & Mahecha, M. D. (2017). Multivariate anomaly detection for Earth observations: a comparison of

algorithms and feature extraction techniques. Earth System Dynamics, 8(3), 677–696. https://doi.org/10.5194/esd-8-677-2017

[10] Goetz, S. J., Baccini, A., Laporte, N. T., Johns, T., Walker, W., Kellndorfer, J., Houghton, R. A., & Sun, M. (2009). Mapping and monitoring carbon stocks with satellite observations: a comparison of methods. Carbon Balance and Management, 4(1). https://doi.org/10.1186/1750-0680-4-2

[11] Gupta, B. B., Gaurav, A., Attar, R. W., Arya, V., Bansal, S., Alhomoud, A., & Chui, K. T. (2024). Advance drought prediction through rainfall forecasting with hybrid deep learning model. Scientific Reports, 14(1). https://doi.org/10.1038/s41598-024-80099-6

[12] Kalogiannidis, S., Kalfas, D., Patitsa, C., & Chalaris, M. (2024). Relationship between Climate Change and Business Risk: Strategies for Adaptation and Mitigation: Evidence from a Mediterranean Country. WSEAS TRANSACTIONS on ENVIRONMENT and DEVELOPMENT, 20, 276–294. https://doi.org/10.37394/232015.2024.20.28

[13] Marios Trigkas, Charitos Evangelos, Karagouni, R., & Anthony, K. (2025). CARBON FARMING IN FORESTRY AND CARBON STORAGE IN WOOD PRODUCTS. THE NEW CERTIFICATION FRAMEWORK AND THE... Sustainable Development, Culture, Traditions Journal, 12(a), 87–98. https://doi.org/10.26341/issn.2241-4010-2025-12a-8-K02252

[14] Matthew, Ajayi, A. S., & Sadiku, J. O. (2025). Predictive Analytics for Supply Chain. ResearchGate, 2394–9333. https://www.researchgate.net/publication/391053236_Predictive_Analytics_for_Supply_Chain

[15] Pratik Sikdar. (2020). Global Forest and Carbon Metrics, 1992-2020. Kaggle.com. https://www.kaggle.com/datasets/pratiksikdar/global-forest-and-carbon-metrics-1992-2020

[16] Pullalarevu, S. T. R., Maggard, A., Narine, L. L., & Peng, Y. (2025). A qualitative assessment of corporate timberland companies' participation in Forest carbon programs. Frontiers in Forests and Global Change, 8. https://doi.org/10.3389/ffgc.2025.1655443

[17] Raj, A. J. (2013). Forest Carbon Sequestration and Carbon Trade. ResearchGate, 710–737. https://www.researchgate.net/publication/377110993_Forest_Carbon_Sequestration_and_Carbon_Trade

[18] Renuka, A. (2025). AI-Driven Predictive Analytics in Precision Agriculture. Scientific Journal of Artificial Intelligence and Blockchain Technologies, 2(3). https://doi.org/10.63345/sjaibt.v2.i3.102

[19] Sofiat Ajide. (2025). Data-Driven Approaches for Supply Chain Resilience: A Review of Predictive Analytics, Optimization, and... ResearchGate, 09(09), 240–260. https://doi.org/10.5281/zenodo.17160644