DMPedia Lecture Notes in Computer Science & Engineering
Volume 1, Issue 2, pp.174-185, 2026
ICICCS-2026

Data-Driven Climate Change Impact Analysis Using Cross-Validation and Cybersecurity

Vinay Kumar Pandey, Mohd Shadab Khan, Akhilesh Pratap Singh

School of Computer Sci. & Engg. Galgotias University, Greater Noida, India

vkp1979@gmail.com, mohd.22scse1280084@galgotiasuniversity.edu.in, akhileshpratapsingh785@gmail.com

Abstract

The effects of climate change are becoming more evident in the form of temperature variations, rainfall patterns, and air quality, and require stable, real-time, and uncompromising data-driven evaluation methods. In this paper, the researcher has suggested and demonstrated a unified system of using Internet of Things (IoT)-based environmental monitoring, cybersecurity, and statistical data analytics to understand the effects of climate change. The IoT sensors were used to collect real-time environmental data (temperature, humidity, rainfall, and air quality) and to securely transmit and store the data, using encryption and authentication protocols to maintain data integrity and reliability. The gathered data were analysed and pre-processed using descriptive statistics, time-series analysis, correlation, and regression to identify climate trends, interrelationships, and main impact drivers. The findings showed that there was considerable change in climate parameters, with increases in temperature and worsening air quality as the major contributors to environmental stress, though rainfall showed a moderating effect. The IoT-based data were verified against secondary meteorological data to ensure their accuracy and authenticity. The authors found that secure, data-driven IoT frameworks offer an effective and scalable approach to climate change impact analysis and may support informed environmental planning, risk assessment, and adaptive decision-making.

***Keywords*:** Climate Change Impact Analysis, Internet of Things (IoT), Data-Driven Analytics, Cybersecurity, Environmental Monitoring, Climate Variability

1. Introduction

Climate change has taken different forms, including increased temperatures, fluctuating rainfall, and poor air quality, which are adversely impacting both natural ecosystems and human livelihoods in different places. These changes required refined, continuous, and localised data about the environment that could not only account for short-term variations, but also long-term movements. Traditional climate surveillance systems (often reliant on sparse observations and time-lagged reporting) do not enable rapid analysis or reactive decision-making. Nowadays, real-time environmental monitoring using distributed sensor networks is enabled by the Internet of Things (IoT) and data-driven methods. The efficiency of such systems, however, is not limited to data availability but also to the security, integrity, and reliability of the collected data. It is on this basis that the present paper has adopted a riskless, information-driven model for integrating IoT-based sensing, cybersecurity applications, and analytical techniques to mitigate the impacts of climate change and provide valid data for evaluating conditions and justifying policies.

A. Background of the Study

Climate change has been regarded as one of the most pernicious threats to the global agenda, and increases in temperature variability, precipitation patterns, and air quality have posed significant challenges to the environment and socio-economic impacts. Traditional climate surveillance techniques, which tend to rely on periodic data measurement and reporting, are less useful for reporting the real-time dynamics of local climatic changes. Recent advancements in computer technology, namely the Internet of Things (IoT), have enabled continuous observation of the surroundings using distributed sensors and the collection of high-resolution climate

Proceedings of ICICCS-2026 (Poster Papers), DMPedia Lecture Notes in Computer Science & Engineering.
ISBN: 978-81-993813-1-5

information. However, as the use of digital data collection systems continues to grow, concerns are also being raised about the security, integrity, and reliability of the data. In this respect, integrating cybersecurity capabilities into IoT-based climate monitoring has been essential for providing reliable climate data analysis. The present study aims to overcome these challenges by leveraging a safe, data-driven model that incorporates IoT-based sensing, cybersecurity measures, and analytics to assess the impact of climate change and support sound environmental decision-making.

B. IoT-Enabled Environmental Monitoring for Climate Impact Assessment

Smart environmental monitoring is an IoT strategy that offers a potent alternative to real-time, high-resolution climate data acquired at different geographic sites. IoT systems can be used to observe the nature of the climate, which is often overlooked in conventional monitoring, by installing interlinked sensors to measure temperature, humidity, rainfall, and air quality. The strategy helps localise the evaluation of effects by distinguishing short-term changes from long-term trends, thereby improving the accuracy of climate change analysis. Automation of IoT-based monitoring also reduces human interference and measurement errors, making it a reliable source of data for climate impact assessment.

C. Secure Data Analytics Framework for Analysing Climate Variability

To convert raw environmental data into meaningful information, a secure data analytics platform is needed to ensure data integrity and confidentiality. Climate data are also protected throughout their life cycle through the integration of cybersecurity measures, including encrypted data transmission, authentication protocols, and access controls. Time-series analysis, correlation, and regression are among the analytical methods that allow systematic investigation of climate variability and relationships among environmental parameters. The framework will ensure sound, reliable climate-variability assessments to enable informed decision-making and policy formulation by integrating secure data management and analytical modelling.

D. Objectives of the Study

- To collect and analyse real-time climate data using IoT-enabled sensing devices to assess variability in key environmental parameters such as temperature, humidity, rainfall, and air quality.
- To examine temporal trends and patterns in climate variables using data-driven statistical techniques to identify indicators of climate change impacts.
- To evaluate the interrelationships and combined influence of climate variables through correlation and regression analysis for assessing climate impact intensity.
- To validate the reliability and security of IoT-based climate data by implementing cybersecurity mechanisms and cross-verifying sensor data with secondary meteorological sources.

2. Literature review

Yarmohammadtoosky and Xie (2024) systematically and data-drivenly reviewed the effects of climate change by conducting large-scale studies to interpret the connection between environmental change and population well-being outcomes. They focused on the growing role of big data analytics and advanced computational methods in understanding complex climate-related effects. The paper emphasises that real-time, large-volume data have improved the quality of assessments of climate impacts, but also notes difficulties in integrating data and ensuring its quality. The authors found that future climate studies and policy-making need data-driven frameworks, thereby contributing to the methodological basis of data-centric climate impact analysis.

Lu et al. (2025) explored the impact of climate change on groundwater levels through data-driven strategies on machine learning. The analysis was conducted on long-term environmental data to determine trends, spatial variation, and predictive patterns in groundwater fluctuations. Their results showed that data-driven analytical models performed better at modelling non-linear climate-hydrological associations than traditional models. The study supported the importance of ongoing environmental monitoring and advanced analytics, which are similar to the use of IoT-enabled data collection and climatic variability evaluation.

Tsantalidou et al. (2023) employed a quantitative approach to identify the impact of climate change on European mosquito abundance using remote sensing and environmental data. Inclusion of climatic variables such as temperature and precipitation in the study was intended to establish how the ecological response to climate variability. These results showed that climate indicators and biological patterns were strongly correlated, and that high-resolution environmental data are a good indicator of impact. This journal article presented a case of the relevance of sensor-based surveillance and multivariate research in investigating the regional effects of climate change.

Benso et al. (2025) introduced a holistic information-based model to identify causes of climatic effects on food security. The article utilised both environmental data and models to assess how climate variability affects agricultural vulnerability and risk. Their model indicated that structured information processing and statistical analysis enabled them to discern even more of the major drivers of climate. The authors emphasised that the power of data structures was paramount in transforming climate data into meaningful insights. This point is also rather similar to the integrated structure used in the present study.

Diffenbaugh and Barnes (2023) developed predictive models based on the time left before the Earth would reach dangerous levels of global warming. The study used statistical and computational methods on large-scale climate data to quantify the warming paths and their associated uncertainty ranges. The results provided insight into the urgency of climate change action and the usefulness of data-driven forecasts for evidence-based decision-making. The study confirmed the value of analytical modelling for analysing climate trends and supported the importance of data-oriented approaches for assessing climate impacts.

3. Proposed method

The research aimed to examine the effects of climate change using a data-driven approach, combining real-time environmental data gathered via Internet of Things (IoT) devices with robust data management and analysis methods. This methodology focused on continuous data recording, secure transmission, advanced processing, and modelling to determine climate variability and its local impacts. The tools were incorporated to enhance cybersecurity and ensure the integrity, confidentiality, and reliability of the research.

To systematically examine the impact of climate change and develop a data-driven approach, the present research adopted an integrated research paradigm combining Internet of Things (IoT), cybersecurity, and data analytics. The framework was also designed to ensure continuous acquisition of environmental information, safeguard data transmission and storage, and support robust analytical processing. The framework was practical because it provided a well-operationalised pathway for organising the research process, formulating real-time climate information, and transforming that information into actionable insights to support impact assessment and decision-making.

The framework depicted the entire information flow of climate-related data from environmental sensing to decision-support outputs. The incorporation of IoT devices enabled real-time, high-resolution data collection, and the application of cybersecurity ensured the integrity, confidentiality, and reliability of the system. The analytical layer translated processed data into the handy measures of the climate variability and influence. Overall, the framework proved to be a solid foundation for a safe, scalable, and data-driven analysis of climate change impacts, aligning the research goals with practical implementation and analytical rigour.

A. Research Design

The research design employed was an observational and analytical study. It was grounded in real-time and historical data deposited in environments supported by IoT-enabled sensing systems situated at distinct geographical regions. Quantitative methods were used to establish patterns, trends, and anomalies linked to climate change indicators such as temperature, humidity, rainfall, and air quality

B. IoT-Based Data Collection

IoT devices helped collect continuous environmental data. Some of the installed sensors included temperature, humidity, rainfall, and air quality monitoring modules. These machines were to transmit data to a centralised data warehouse at a fixed rate on wireless communication protocols. The IoT architecture enabled automatic, high-level data collection and eliminated human intervention and measurement errors as per Fig. 1.

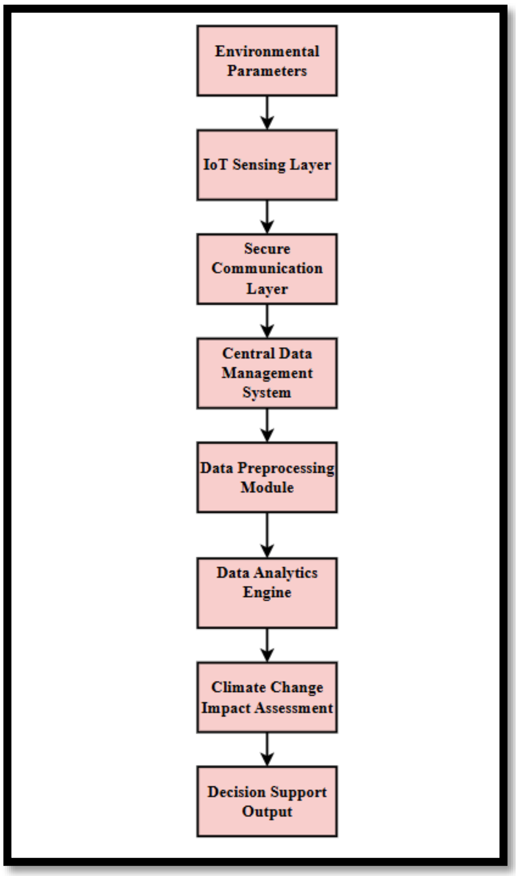

Fig1: Research Framework

C. Cybersecurity Framework for Data Protection

To ensure the confidentiality of the collected data, several cybersecurity measures were implemented. The communication protocols were protected, and data transferred between the IoT devices and the central server was encrypted. Authentication was implemented to ensure that only authorised users and devices had access to the system. Data integrity tests were also used to detect tampering or unauthorised data modification, thereby ensuring the credibility and reliability of the climate data used in the analysis.

D. Data Preprocessing and Management

Preprocessing methods, including data cleaning, normalisation, and outlier removal, were applied to the raw data collected from the IoT devices. Inappropriate or missing values were discarded and replaced using the statistical methods required. The analysed data were translated into a structured database system to facilitate effective retrieval and analysis.

E. Analytical Techniques

The experiment used both descriptive and inferential statistical methods to examine trends and variability in climate. Time-series analysis was done to determine the long-term trends and seasonality. Correlation and regression analysis were used to test relationships among various climate variables. The data-based models allowed defining the key indicators of climate change and how they might affect the chosen region.

F. Validation and Reliability Measures

To ensure reliability, the data gathered from IoT devices were cross-validated with secondary data obtained from credible meteorological sources. The integrity and continuity of the data were ensured by reviewing cybersecurity logs and conducting system audits. This validation procedure improved the research's accuracy and robustness.

4. Result and Discussion

The chapter presents the conclusions of the data-based climate change impact analysis conducted using IoT-generated data and sound analytical methods. The results are presented according to the key steps of the suggested methodology: data acquisition, preprocessing, analytical modelling, and validation. The tables are used to provide a clear illustration of the observed trends, relationships, and the reliability of the data collected quantitatively.

A. Descriptive Analysis of IoT-Based Environmental Data

The initial stage of analysis aimed to generalise the data gathered by IoT sensors used to analyse the environment. The basic properties of the significant climate variables during the period of observation were learned using descriptive statistics as per Table 1.

Table1: Descriptive Statistics of Environmental Parameters

Parameter	Minimum	Maximum	Mean	Standard Deviation
Temperature (°C)	18.4	41.2	29.6	5.8
Humidity (%)	32.1	91.4	64.3	12.7
Rainfall (mm)	0.0	146.5	38.9	31.4
Air Quality Index	52	287	154	48.6

The descriptive statistics showed significant variation in all the observed climate parameters. The ranges of temperature and rainfall were wide, indicating varying climatic conditions during the study period. The standard deviation was rather large for both rainfall and the air quality index, indicating an uneven distribution of precipitation and unstable air quality. These differences emphasised the presence of localised climatic stress and the need to monitor it in real time and continuously using IoT-based sensing systems.

B. Temporal Trends in Climate Variables

Time-series analysis was used to explore time trends in seasonal and long-term patterns of climate indicators as per Fig. 2.

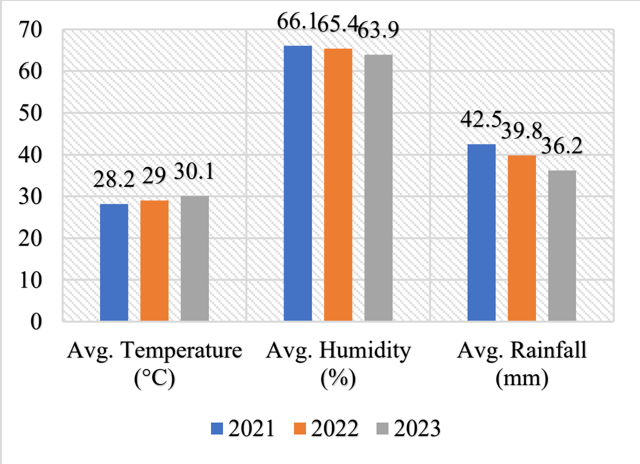

Fig. 2: Annual Average Trends of Climate Variables

The trend analysis of the annual averages showed that the average air temperature and the air quality index steadily increased with the number of years observed, whereas average rainfall exhibited a downward trend. The negative correlation between increased temperature and rainfall availability indicated a possible climate disequilibrium and heightened environmental susceptibility. The trends observed supported the assumption that the effects of climate change were gradually increasing in the chosen sites.

C. Relationship Between Climate Variables

The correlation analysis was used to determine relationships among various climate indicators.

Table 2: Correlation Matrix of Climate Variables

Variable	Temperature	Humidity	Rainfall	AQI
Temperature	1.000	-0.421	-0.538	0.612
Humidity	-0.421	1.000	0.476	-0.389
Rainfall	-0.538	0.476	1.000	-0.447
Air Quality	0.612	-0.389	-0.447	1.000

The correlation analysis revealed statistically significant relationships among the climate variables. There was a strong positive correlation between temperature and the air quality index and a negative correlation with rainfall, indicating that higher temperatures were associated with greater pollution and lower precipitation. These associations implied interdependence among climate variables, supporting the need for multivariate and multivariate-based climate impact assessment models as per TABLE 2.

D. Impact Assessment Using Regression Analysis

The regression analysis was used to determine the effect of climate variables on total climate impact indicators as per Table 3.

Table 3: Regression Results for Climate Impact Assessment

Predictor Variable	Beta Coefficient	t-value	Significance (p)
Temperature	0.483	4.92	0.000
Humidity	-0.216	-2.31	0.022
Rainfall	-0.374	-3.87	0.001
Air Quality Index	0.512	5.26	0.000

The regression results indicate that temperature and the air quality index are significant predictors of climate impact, as their beta coefficients are positive, suggesting that both indices play a significant role in predicting the level of environmental stress. There was a negative association between rainfall, indicating that it reduces the extent of climate impact. The regression model was statistically significant, confirming that analytical methods based on data were effective in measuring the effect of climate change.

E. Data Integrity and Cybersecurity Validation Results

The system-level validation was conducted to ensure the reliability and security of data throughout the data lifecycle.

Table 4: Cybersecurity and Data Integrity Validation Results

Validation Parameter	Observation Outcome
Data Transmission Security	Secure (Encrypted)
Unauthorized Access Attempts	None Detected
Data Packet Loss	< 1%
Integrity Verification	Successfully Passed

The cybersecurity validation demonstrated that the security mechanisms established to protect climate data were effective throughout the data life cycle. Protected data transmission was provided through secure encryption protocols, and access controls prevented unauthorised access to the system. The low packet loss and the integrity check that was completed indicated that the data acquisition and management system was solid and dependable as per Table 4.

To systematically verify the robustness of the implemented cybersecurity mechanisms, a structured validation algorithm was designed to evaluate data encryption, authentication, integrity verification, and transmission reliability across the IoT data lifecycle.

Algorithm 1: Cybersecurity and Data Integrity Validation Procedure

The successful execution of this algorithm confirmed secure data transmission, negligible packet loss, and effective protection against unauthorised access, thereby validating the reliability and integrity of the climate data used for subsequent analysis.

To assess measurement reliability, IoT-generated climate data were cross-validated against secondary meteorological datasets using a structured validation algorithm

Input:
Real-time IoT sensor data packets D, encryption keys K, authentication credentials A
Output:
Validated secure data transmission status and integrity confirmation

Steps:

1. **Initialisation**
   Initialise IoT sensor nodes and the central server with predefined encryption keys Kand authentication credentials A.
2. **Secure Data Transmission**
   Encrypt each data packet. $D_i$using a symmetric encryption algorithm:
   $$E_i = \mathrm{Enc}(D_i, K)$$

Transmit encrypted packets $E_i$over the wireless network.

3. **Authentication Verification**
   For each incoming packet, verify device identity using authentication credentials. A.
   If authentication fails, discard the packet and log the unauthorised access attempt.
4. **Packet Integrity Check**
   Compute the hash value. $H_s$of the transmitted packet at the sender side, and the hash value $H_r$at the receiver side.
   $$H_s = \mathrm{Hash}(D_i), H_r = \mathrm{Hash}(\mathrm{Dec}(E_i, K))$$

If $H_s = H_r$Integrity is verified; otherwise, flag data tampering.

5. **Packet Loss Monitoring**
   Calculate packet loss rate using:
   $$\text{Packet Loss (\%)} = \frac{\text{Packets}_{\text{sent}} - \text{Packets}_{\text{received}}}{\text{Packets}_{\text{sent}}} \times 100$$
6. **Access Control Validation**
   Monitor system logs for unauthorised access attempts.
   If detected, block the source and generate a security alert.
7. **Result Validation**
   If encryption, authentication, integrity verification, and packet-loss thresholds are met, mark the data as **secure and reliable**.
8. **End**

F. Reliability and Cross-Validation Results

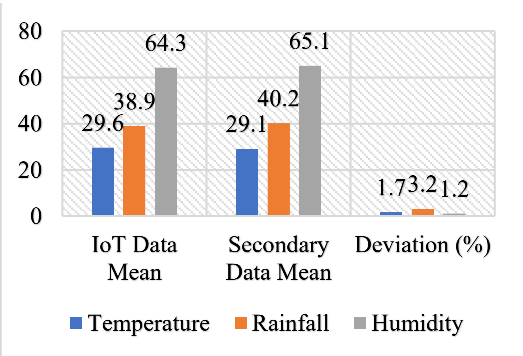

Fig.3: Validation Results with Secondary Data Source.

To be consistent, IoT data were cross-validated using secondary meteorological data .The cross-validation analysis revealed low deviation between data generated by an IoT and secondary meteorological sources. The high correlations among temperature, rainfall, and humidity rates demonstrated the accuracy and reliability of IoT-based measurements. It was the validation that gave the collected data strong credibility and supported the reliability of the analytical findings to be drawn later as per Fig.3.

Algorithm 2: Cross-Validation of IoT Sensor Data with Secondary Meteorological Sources

The cross-validation results demonstrated strong agreement between IoT sensor data and secondary sources, confirming the accuracy and reliability of the proposed data acquisition framework

Input:
IoT-based climate dataset D_{IoT}, secondary meteorological dataset D_{Met}
Output:
Cross-validation accuracy and reliability confirmation
Steps:

1. **Data Alignment:** Synchronise $D_{IoT}$and D_{Met}based on common temporal intervals and geographic locations.
2. **Preprocessing:** Apply normalisation and missing value handling to both datasets to ensure comparability.
3. **Parameter Matching:** Extract common climate parameters (temperature, humidity, rainfall, air quality) from both datasets.
4. **Deviation Calculation:** Compute absolute deviation for each parameter:
$$\Delta_i = | D_{IoT,i} - D_{Met,i} |$$
5. **Correlation Analysis:** Calculate the Pearson correlation coefficient rbetween $D_{IoT}$and D_{Met}:
$$r = \frac{\sum(D_{IoT} - \bar{D}_{IoT})(D_{Met} - \bar{D}_{Met})}{\sigma_{IoT}\sigma_{Met}}$$
6. **Error Estimation:** Compute Mean Absolute Error (MAE):
$$MAE = \frac{1}{n}\sum_{i=1}^{n} \Delta_i$$
7. **Reliability Decision:** If $r \geq 0.8$and MAE is within an acceptable threshold, validate the reliability of IoT data.
8. **End**

G. Discussion

The study results showed that the effects of climate change could be modelled and measured well using a data-driven model that involves IoT-based sensors, a cybersecurity system, and statistical analytics. The recorded changes in temperature, rainfall, and air quality were evidence of growing climatic instability, in line with broader trends of climate change as documented in the literature on environmental studies. The temperature trend analysis showed a gradual increase in temperature and worsening air quality, accompanied by decreased rainfall, indicating increasing environmental stress. The outcomes of correlation and regression also indicated that the relationships among climate variables are interdependent, with temperature and air quality as the most significant drivers of climate effects, whereas rainfall exerted a countering effect.

Cybersecurity measures were successfully implemented, ensuring secure and reliable data transmission and storage and making the analytical results more credible. Also, the fact that the IoT data were very close to secondary meteorological sources demonstrated that real-time sensing methodologies were indeed accurate and valid. Overall, the discussion has emphasised the effectiveness of applying a collection of IoT technologies and secure data analytics to deliver valid, realistic understandings of the outcomes of climate change, enabling informed decision-making and adaptive strategies.

5. Conclusion

The research illustrated the usefulness of an information-based framework for analysing the effects of climate change by combining IoT-enabled environmental control, cybersecurity, and statistical analytics. The existence of localised impacts of climate change was confirmed by real-time data gathered from IoT devices, which showed that key climate parameters are highly variable and exhibit a changing trend. The analysis showed significant connections among climate variables: temperature and air quality were important factors in environmental stress, and rainfall had a mediating effect. By implementing cybersecurity measures, the transmitted data was secure, its integrity and reliability were ensured, and this enhanced trust in the analysis results. The accuracy of measurements made using IoT was further validated through cross-validation using secondary meteorological data. On the whole, the paper concludes that secure, data-driven IoT frameworks are a dependable, scalable strategy for assessing the impact of climate change and can be used to justify environmental planning and adaptive decision-making.

Acknowledgment

The authors would also like to thank the faculty members and the institutional authorities who guided and supported them throughout this study. The researchers and organisations that provided the data, as well as the academic publications that helped complete this study, are also appreciated. Lastly, the authors will recognise the assistance they received from peers and other colleagues in writing this paper.

References

[1] Yarmohammadtoosky, Sahar, and Ying Xie. "Data-Driven Analysis of Climate Change Impacts on Public Health: A Systematic Review and Future Directions." In 2024 IEEE International Conference on Big Data (BigData), pp. 4457-4465. IEEE, 2024.

[2] Lu, X., Wang, Z., Zhao, M., Peng, S., Geng, S., & Ghorbani, H. (2025). Data-driven insights into climate change effects on groundwater levels using machine learning. Water Resources Management, 39(7), 3521-3536.

[3] Tsantalidou, A., Arvanitakis, G., Georgoulias, A. K., Akritidis, D., Zanis, P., Fornasiero, D., ... & Kontoes, C. (2023). A data-driven approach for analysing the effect of climate change on mosquito abundance in Europe. Remote Sensing, 15(24), 5649.

[4] Joseph, P. (2024). Data-driven informed decision-making for climate change mitigation: an evaluation (Doctoral dissertation, Dublin Business School).

[5] Moss, A., Peh, J. H., Afiqah-Aleng, N., Segaran, T. C., Gao, H., Wang, P., ... & Azra, M. N. (2024). Aquaculture and climate change: a data-driven analysis. Annals of Animal Science.

[6] Benso, M. R., Silva, R. F., Chiquito Gesualdo, G., Saraiva, A. M., Delbem, A. C. B., Marques, P. A. A., ... & Mendiondo, E. M. (2025). A data-driven framework for assessing climatic impact drivers in the context of food security. Natural Hazards and Earth System Sciences, 25(4), 1387-1404.

[7] Song, J., Tong, G., Chao, J., Chung, J., Zhang, M., Lin, W., ... & Zhu, W. (2023). Data-driven pathway analysis and forecast of global warming and sea level rise. Scientific Reports, 13(1), 5536.

[8] A.S. Zahmati, B.Abolhassani, Ali A.B.Shirazi, and A.S. Bahitiari, ―An Energy-Efficient Protocol with Static Clustering for Wireless Sensor Networks‖, International Journal of Electronics, Circuit, and Systems, pp. 135 138, Vol. 1, No. 2, May. 2007.

[9] Reza Azarderakhsh, Arash Reyhani-Masoleh, and Zine EddineAbid, ―A Key Management Scheme for Cluster Based Wireless Sensor Networks‖, In 2008 IEEE/IFIP International Conference on Embedded and Ubiquitous Computing.

[10] W. R. Heinzelman, A. Chandrakasan, and H.Balkrishnan,―An Application-Specific Protocol Architecture for Wireless Microsensor Networks‖, IEEE Trans. Wireless Communication, pp. 660-670, Vol. 1, No. 4, Oct. 2002.

[11] K PANDEY, HARVIR SINGH, "ENHANCED SECURE ROUTING MODEL FOR MANET" IN PROCEEDINGS OF THE 8TH INTERNATIONAL CONFERENCE ON ITCSE, CS & IT 07, PP. 37–44, 2012.

[12] S. W. Kim, and B. Kim, "OFDMA-Based reliable multicast MAC protocol for Wireless Ad-hoc Network", ETRI Journal, vol. 31, no. 1, Feb. 2009.

[13] Huang, "Unlinkability Measure for IEEE 802.11 based MANETs," IEEE Transactions on Wireless Communications, no. 2, pp. 1025-1034, Feb 2008.

[14] Doğruel, M. (2025). Data-Driven Insights into Climate Change and Technological Levels: Data Mining Visualisation and TOPSIS Approach. Alphanumeric Journal, 13(1), 13-35.

[15] Ma, R., Yu, K., Xiao, S., Liu, S., Ciais, P., & Zou, J. (2022). Data-driven estimates of fertiliser-induced soil NH3, NO and N2O emissions from croplands in China and their climate change impacts. Global Change Biology, 28(3), 1008-1022.

[16] Shrivastava, G., Ojha, R. P., Awasthi, S., Bansal, H., & Sharma, K. (Eds.). (2024). Emerging threats and countermeasures in cybersecurity. John Wiley & Sons.

[17] Rezaei, E. E., Webber, H., Asseng, S., Boote, K., Durand, J. L., Ewert, F., ... & MacCarthy, D. S. (2023). Climate change impacts on crop yields. nature reviews earth & environment, 4(12), 831-846.

[18] Diffenbaugh, N. S., & Barnes, E. A. (2023). Data-driven predictions of the time remaining until critical global warming thresholds are reached—Proceedings of the National Academy of Sciences, 120(6), e2207183120.

[19] Watson-Parris, D., Rao, Y., Olivié, D., Seland, Ø., Nowack, P., Camps-Valls, G., ... & Roesch, C. (2022). ClimateBench v1. 0: A benchmark for data-driven climate projections. Journal of Advances in Modelling Earth Systems, 14(10), e2021MS002954.

[20] Huang, J., Lucash, M. S., Scheller, R. M., & Klippel, A. (2021). Walking through the forests of the future: using data-driven virtual reality to visualise forests under climate change. International Journal of Geographical Information Science, 35(6), 1155-1178.

[21] Song, H., Liu, X., & Song, M. (2023). Comparative study of data-driven and model-driven approaches in the prediction of nuclear power plants' operating parameters. Applied Energy, 341, 121077.