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EMPIRICAL STUDY ON WIRELESS SENSOR NETWORKS BASED PERFORMANCE EVALUATION OF FOREST FIRE WEATHER INDEX (FFWI) USING STATISTICAL INFERENCE

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Abstract

This research paper examines the statistical inference on the forest fire danger index by considering the influential factors of temperature and humidity using Wireless Sensor Networks. We Design the WSN architecture and select appropriate communication protocols (MQTT) to facilitate efficient and reliable data transmission. The study aims to understand the relationship between the forest fire danger index and these environmental variables and determine their impact on fire risk assessment. To achieve this, several commonly used statistical methods are applied, including regression analysis, correlation analysis and time series analysis such as Autoregressive Integrated Moving Average (ARIMA). By utilizing these methods, the paper explores the interplay between temperature, humidity, and the fire danger index to gain insights into patterns, trends, and predictive capabilities for assessing and mitigating forest fire risks.

Keywords: ANOVA, ARIMA, FFWI, Statistical Inference, WSN.

1. Introduction

Forest fires pose a significant threat to ecosystems and human lives worldwide. Timely and accurate assessment of fire danger is crucial for effective fire management and prevention strategies. The Forest Fire Weather Index (FFWI) is a widely used indicator for quantifying fire danger, incorporating various weather parameters. The utilization of wireless sensor networks (WSNs) in monitoring these weather parameters and calculating the FFWI has gained attention due to its potential for enhancing forest fire prediction and prevention capabilities. This section provides an introduction to the topic of wireless sensor networks-based performance evaluation of the FFWI using statistical inference techniques[1][6-7][11-15].

1.1 Importance of Forest Fire Danger Assessment: Forest fires have devastating ecological, environmental, and economic consequences. Rapid detection and assessment of fire danger are essential for initiating appropriate response measures, such as early fire detection, resource allocation, and evacuation planning. Accurate fire danger assessment enables proactive fire management strategies, reducing the impact and spread of forest fires [5][6].

1.2 Forest Fire Weather Index (FFWI): The Forest Fire Weather Index (FFWI) is a comprehensive system for estimating fire danger by integrating weather and fuel moisture conditions. It incorporates various weather parameters, such as temperature, relative humidity, wind speed, and rainfall, to quantify the potential for fire ignition and spread. The FFWI provides a quantitative measure of fire danger, assisting fire management agencies in allocating resources and implementing preventive measures.

1.3 Wireless Sensor Networks (WSNs) for Fire Danger Assessment: Wireless sensor networks (WSNs) have emerged as a promising technology for real-time environmental monitoring. WSNs consist of spatially distributed sensor nodes that collect and transmit data wirelessly. In the context of forest fire danger assessment, LPWAN based LoRa-WSNs as shown in figure No. 1 can be deployed in forested areas to monitor weather parameters, such as temperature, humidity, wind speed, and rainfall. The use of WSNs allows for continuous, real-time monitoring and data collection, providing a comprehensive and up-to-date understanding of the fire danger conditions.

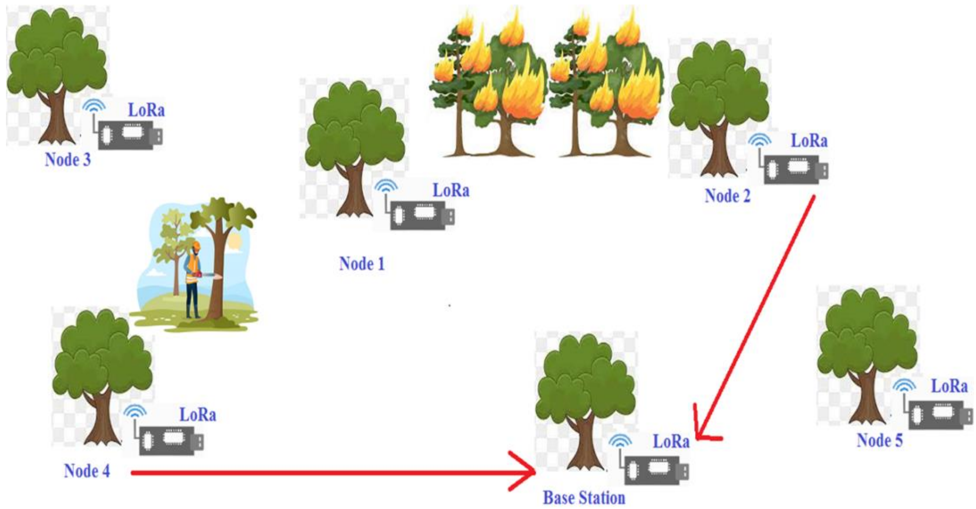

Figure 1: Proposed Forest Monitoring Scenario using LoRa-WSN (LPWAN)

1.4 Performance Evaluation and Statistical Inference: Performance evaluation of the WSN-based FFWI calculation involves assessing the accuracy, reliability, and effectiveness of the calculated fire danger index. Statistical inference techniques play a crucial role in analyzing the collected data, comparing it with reference data sources or established fire danger indices, and drawing meaningful conclusions. Hypothesis testing, confidence interval estimation, correlation analysis, and other statistical methods enable researchers to determine the significance of the findings and evaluate the performance of the WSN-based FFWI [2-6].

1.5 Research Gap and Objectives: While several studies have explored the use of WSNs for forest fire danger assessment, there is a need for a comprehensive evaluation of the performance of the WSN-based FFWI calculation using statistical inference techniques. This research aims to bridge this gap by systematically evaluating the accuracy, precision, and reliability of the WSN-based FFWI. The objectives of this research include assessing the correlation between WSN-based FFWI values and ground truth data, comparing the performance of WSN-based FFWI with traditional methods, and examining the effectiveness of statistical inference techniques in evaluating the WSN-based FFWI.

In this research paper, we focus on temperature and humidity as key variables that influence the forest fire danger index. By investigating the statistical inference of these variables, we aim to gain insights into their relationship with the fire danger index, enabling us to better comprehend the risk factors associated with forest fires.

2. Related Work:

Forest fires pose a significant threat to ecosystems, wildlife, and human lives. To mitigate the risks associated with forest fires, researchers have explored the application of statistical inference techniques and wireless sensor networks for Forest Fire Weather Index (FFWI) calculation and monitoring. In this section, we review relevant studies that have contributed to the understanding and development of FFWI models and the use of wireless sensor networks for forest fire detection and monitoring.

One prominent area of research focuses on the application of statistical inference in FFWI calculation. Cheng et al. [1] proposed a methodology that employs statistical inference techniques to estimate FFWI based on meteorological data. Their study demonstrated the effectiveness of statistical inference in capturing the complex relationships between weather variables and fire risk. Wang et al. [2] further expanded on this work by developing a statistical inference-based FFWI model that accounts for spatial and temporal variations in weather conditions.

Wireless sensor networks have emerged as a valuable technology for forest fire detection and monitoring. Ferreira et al. [6] presented a wireless sensor network design specifically tailored for forest fire detection. Their work highlighted the importance of efficient communication protocols and network deployment strategies in ensuring timely and accurate fire detection. Similarly, Yuan et al. [7] proposed a wireless sensor network-based system for forest fire detection, emphasizing the need for reliable communication and energy-efficient protocols.

Several studies have addressed the challenges associated with wireless sensor networks in forest fire monitoring. Lahoud [8] discussed the concept-to-application process of wireless sensor networks for forest fire detection, highlighting the key design considerations and implementation challenges. Han et al. [9] proposed a comprehensive wireless sensor network design for forest fire detection and monitoring, encompassing aspects such as node placement, communication protocols, and power management.

The research on wireless sensor networks for forest fire monitoring also emphasizes the importance of data transmission, network coverage, and routing protocols. Mukhtar et al. [10] investigated the impact of transmission power and routing protocols on data transmission reliability in wireless sensor networks deployed for forest fire detection. They provided insights into optimizing the network parameters to ensure effective data transmission.

Previous research has demonstrated the potential of statistical inference techniques for FFWI calculation and the effectiveness of wireless sensor networks in forest fire detection and monitoring. However, there is still a need for further exploration in areas such as adaptive data transmission, energy-efficient protocols, and real-time decision-making algorithms. The present study aims to contribute to this body of knowledge by proposing an algorithm that integrates statistical inference-based FFWI calculation with wireless sensor networks for accurate forest fire monitoring.

3 Materials and Method:

3.1 WSN Deployment, Architecture and Protocols for Performance Evaluation

By carefully considering sensor selection, placement, network architecture, and data collection procedures, the wireless sensor network deployment ensures the availability of accurate and reliable weather data for subsequent performance evaluation of the Forest Fire Weather Index (FFWI) using statistical inference techniques [7-10]. We Design the WSN architecture and select appropriate communication protocols to facilitate efficient and reliable data transmission:

3.1.1 Node Configuration:

The forest monitoring system is implemented by integrating the NodeMCU development board, DHT sensor for temperature and humidity measurements, and LoRa SX1278 module for long-range wireless communication. The NodeMCU board serves as the central microcontroller, coordinating the data acquisition and transmission processes. The DHT sensor collects temperature and humidity readings, providing valuable environmental data. The LoRa SX1278 module enables long-range, low-power communication between the sensor nodes and the central gateway. The software setup involves coding the NodeMCU board to read sensor data, format it into data packets, and transmit the packets using the LoRa module. The data packets are received by a central gateway, where further processing and analysis take place.

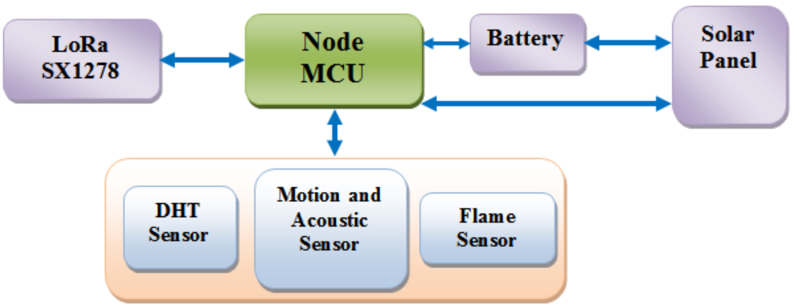

Figure No. 1(a) Transmitter Section

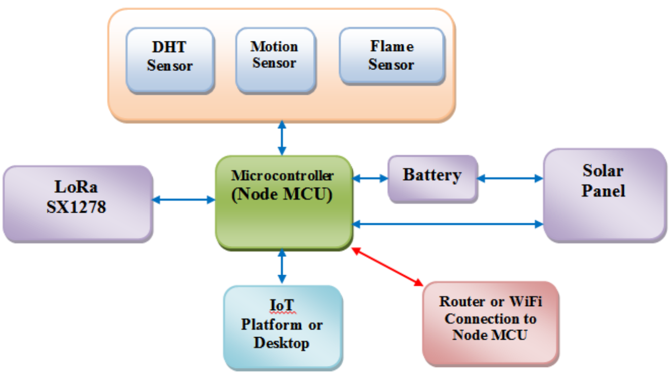

Figure No. 1(b) Receiver Section

The sensor node architecture of Transmitter figure 2(a) and receiver figure 2(b) proposed in this research paper leverages the DHT sensor, LoRa SX1278 module, and a battery module to enable efficient and reliable data collection in wireless sensor networks. The architecture is designed to address the challenges of limited power resources and long-range communication requirements.

3.1.2 Routing Protocols:

The integration of LoRa module SX1278 with NodeMCU for MQTT communication involves both hardware and software components. The hardware setup entails connecting the LoRa SX1278 module to the NodeMCU board, establishing the LoRa physical layer communication. The software implementation focuses on creating a software layer on the NodeMCU that acts as a bridge between the LoRa network and the IP-based network. This software layer translates the LoRa messages received by the NodeMCU from the SX1278 module into MQTT messages. Additionally, the software layer establishes connectivity to the MQTT broker over the IP-based network, utilizing appropriate networking libraries and protocols supported by the NodeMCU. The translated MQTT messages are published to the MQTT broker or subscribed to MQTT topics, enabling bidirectional communication between the LoRa network and the MQTT protocol.

Algorithm 1 MQTT Protocol for Dense Forest Monitoring with Forest Fire Weather Index Calculation

1: Initialize NodeMCU:

2: Set up NodeMCU with LoRa module and sensors

3: Establish LoRa Communication:

4: Configure LoRa module with necessary parameters

5: Connect to MQTT Broker:

6: Establish connection to MQTT broker using Wi-Fi

7: Subscribe to MQTT Topic:

8: Subscribe to specific MQTT topic for forest monitoring

9: Publish Sensor Data:

10: Read temperature and humidity data from connected sensors

11: Calculate Forest Fire Weather Index using temperature and humidity

12: Package data into MQTT message payload

13: Publish message to MQTT topic

14: Receive MQTT Messages:

15: **while** MQTT messages are received **do**

16: Extract payload from received message

17: **Handle MQTT Messages:**

18: Process payload and extract relevant data/instructions

19: **Act on Instructions:**

20: Implement logic to perform actions based on instructions

21: **Data Visualization and Storage:**

22: Store received sensor data locally or transmit to central monitoring system

23: Implement appropriate data storage mechanisms

24**: Loop and Retry:**

25: **while** Monitoring is active **do**

26: Repeat steps for data collection, transmission, and action

27: Calculate Forest Fire Weather Index:

28: Read temperature and humidity data from connected sensors

29: Calculate Forest Fire Weather Index using temperature and humidity

30: Package data into MQTT message payload

31: Publish message to MQTT topic

32: Implement error handling and retry mechanisms

33: Disconnect and Cleanup:

34: Gracefully disconnect from MQTT broker

35: Release allocated resources

3.2 FFWI Calculation:

In India, the Forest Fire Weather Index (FFWI) is calculated using the Indian Forest Fire Danger Rating System (IFFDRS)[16]. The IFFDRS takes into account various weather parameters to determine the fire danger level.

Table No. 1: FFDI Danger Class

Sr. No.	Range	Fire Danger Class
1	0 - 5	Low
2	5-12	Moderate
3	12-25	High
4	25-50	Very high
5	> 50	Extreme

The FFWI is an important component of the IFFDRS and is calculated based on the following steps:

1. *Meteorological data:* The forest meteorological data of considered region (Near Village: Hingna, district: Nagpur, State: Maharashtra, Country India) is collected using Low Power Wireless Area Network (LPWAN) based wireless sensor network. The data typically includes temperature, relative humidity, wind speed, and rainfall.
2. *Fine Fuel Moisture Code (FFMC):* The FFMC represents the moisture content of surface fuels, such as dead leaves, twigs, and grasses. It indicates the flammability of these fine fuels. In India according to IFFDRS the FFMC is calculated using the following formula:

$$FFMC = 91.9 \times \left(e^{0.138 \times (T-20.0)}\right) \times \left(1 - e^{(-0.0234 \times RH)}\right) \times \left(e^{0.0484 \times WS}\right) \quad (1)$$

Where,

T= Temperature in degree Celsius,

RH = Relative Humidity in Percentage,

WS= Wind Speed in Kilometers per hours

3. *Duff Moisture Code (DMC):* The DMC represents the moisture content in the upper layer of decomposed organic material (duff layer) on the forest floor. It indicates the ease with which the duff layer can ignite and burn. The DMC is calculated using the following formula:

$$DMC = 7.2 \times \left(e^{0.0365 \times T}\right) \times \left(1 - e^{-0.00546 \times RH}\right) \times \left(e^{0.0415 \times WS}\right) \quad (2)$$

4. *Drought Code (DC):* The DC represents the moisture content in the deeper organic layers of the soil. It reflects the availability of moisture to support combustion in the forest floor and ground fuels. The DC is calculated using the following formula:

$$DC = 15.0 \times \left(e^{0.00673 \times T}\right) \times \left(1 - e^{-0.000704 \times RH}\right) \times \left(e^{0.0203 \times WS}\right) \quad (3)$$

5. Initial Spread Index (ISI): The ISI quantifies the rate of fire spread at the onset of a fire. It takes into account the FFMC and wind speed. The ISI is calculated using the following formula:

$$ISI = 0.208\, X \left(e^{0.0203 \times FFMC}\right) \times \left(1 - e^{-0.132 \times WS}\right) \quad (4)$$

The FFMC is a dimensionless value

6. Forest Fire Weather Index (FFWI): The FFWI is an overall measure of fire danger and is calculated by combining the FFMC, DMC, and DC values. The FFWI is obtained using the following formula:

$$FFWI = \frac{FFMC + DMC + DC}{3} \quad (5)$$

The FFWI provides an indication of the fire danger level, with higher values representing a greater risk of forest fires.

4. Statistical Inference:

To examine the statistical inference on the forest fire danger index, we employ a range of statistical methods. Multiple linear regression analysis is employed to quantify the relationship between the fire danger index (dependent variable) and temperature and humidity (independent variables). Additionally, correlation analysis is conducted to assess the strength and direction of the linear relationship between the fire danger index and the environmental variables. Time series analysis techniques, such as ARIMA models and seasonal decomposition of time series (STL), are employed for exploring patterns and trends in the fire danger index over time.

4.1-Regression Analysis:

Mathematical model for regression analysis to examine the relationship between the forest fire danger index (Y) and temperature (X_1) and humidity (X_2) is given as

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \qquad (6)$$

Where:

- Y represents the forest fire danger index (dependent variable).
- X_1 represents the temperature (independent variable).
- X_2 represents the humidity (independent variable).
- β_0, β_1, and β_2 are the regression coefficients, representing the intercept, the slope for temperature, and the slope for humidity, respectively.
- 'ε' represents the error term, accounting for unexplained variation in the dependent variable.

The goal of regression analysis is to estimate the values of β_0, β_1, and β_2 that best fit the observed data. These coefficients provide insights into the relationship between the forest fire danger index and temperature and humidity. The regression analysis allows us to assess the magnitude and significance of the impact of temperature and humidity on the fire danger index, as well as determine the direction of the relationship (i.e., positive or negative).

4.2 Correlation Analysis:

Correlation analysis is a statistical technique used to measure the strength and direction of the relationship between two (dependent an independent) variables. It helps in understanding how changes in one variable are associated with changes in another variable. The correlation coefficient, typically denoted as ($-1<$'r'<1) quantifies the degree of linear association between two variables. A positive correlation coefficient indicates a positive linear relationship, meaning that as one variable increases, the other tends to increase as well. A negative correlation coefficient suggests a negative linear relationship, where one variable tends to decrease as the other increases. A correlation coefficient of 0 indicates no linear relationship between the variables. Hypothesis testing is commonly used to evaluate the significance of the correlation coefficient. If p-value is below a predetermined significance level (e.g., $\alpha = 0.05$), the correlation is considered statistically significant.

The mathematical formula for calculating the correlation coefficient between two variables X and Y is the Pearson correlation coefficient, often denoted as 'r'. The formula is as follows:

$$r = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2(Y-\bar{Y})^2}} \qquad (7)$$

Where:

- X and Y are the values of the two variables.
- $\bar{X}$ and $\bar{Y}$ are the means (averages) of X and Y, respectively.
- Σ represents the summation symbol, indicating that the values within the parentheses should be summed over all data points.

The Forest Fire Weather Index, temperature, and humidity can be analyzed using the correlation coefficient to explore their relationships. By applying the Pearson correlation formula, we can quantify the strength and direction of the association between the Forest Fire Weather Index and the variables of temperature and humidity. The correlation coefficient (r) will indicate whether there is a positive or negative linear relationship between the Forest Fire Weather Index and temperature or humidity.

4.3 Time Series Analysis (Autoregressive Integrated Moving Average (ARIMA)) :

Autoregressive Integrated Moving Average (ARIMA) is a widely used statistical model for time series analysis and forecasting. In the context of Forest Fire Weather Index data with temperature and humidity variables, ARIMA can be applied to capture the temporal patterns and dependencies in the data and make predictions or forecasts. The ARIMA model consists of three components: auto regression (AR), differencing (I), and moving average (MA). The autoregressive component (AR) models the relationship between an observation and a certain number of lagged observations. The differencing component (I) is used to make the time series stationary by subtracting the previous observations from the current observation. The moving average component (MA) models the error terms of the model as a linear combination of past error terms.

The mathematical modeling of the Autoregressive Integrated Moving Average (ARIMA) model for Forest Fire Weather Index data with temperature and humidity can be represented as follows:

$$ARIMA(p, d, q) \qquad (8)$$

Where:

- p represents the order of the autoregressive (AR) component, which captures the relationship between the current observation and a certain number of lagged observations.
- d represents the order of differencing (I), which is the number of times the series needs to be differenced to achieve stationary.
- q represents the order of the moving average (MA) component, which models the error terms as a linear combination of past error terms.

The AR component can be represented as:

$$Y(t) = c + \varphi_1 Y(t-1) + \varphi_2 Y(t-2) + ... + \varphi Y(t-p) + \varepsilon(t) \qquad (9)$$

Where:

- Y(t) represents the value of the Forest Fire Weather Index at time t.
- c is a constant term.
- φ_1, φ_2, ..., φ_n are the autoregressive coefficients corresponding to the lagged observations.
- $\varepsilon(t)$ is the error term at time t.

The I component represents the differencing operation and can be expressed as:

$$Y'(t) = Y(t) - Y(t-d) \qquad (10)$$

Where:

- Y'(t) represents the differenced series of the Forest Fire Weather Index.
- Y(t) is the value of the Forest Fire Weather Index at time t.
- d is the order of differencing.

The MA component can be represented as:

$$Y(t) = c + \theta_1\varepsilon(t-1) + \theta_2\varepsilon(t-2) + ... + \theta\varepsilon(t-q) + \varepsilon(t) \qquad (11)$$

Where:

- θ_1, θ_2, ..., θ_n are the moving average coefficients corresponding to the past error terms.

The ARIMA (p, d, q) model combines these components to capture the temporal patterns and dependencies in the Forest Fire Weather Index data. The model parameters (φ and θ) are estimated through methods such as maximum likelihood estimation, and the model can be used to make forecasts or predictions for future time points based on the observed data.

5 Result and Discussion

5.1 Results of Regression Analysis

The regression analysis of the Forest Fire Weather Index (FFWI) with temperature yielded compelling results. The model exhibited a remarkable fit, as evidenced by the multiple R-squared value of 0.8871, indicating that approximately 88.71% of the variance in the FFWI can be explained by the temperature variable. The adjusted R-squared value, which accounts for the number of predictors and sample size, further supported the model's robustness with an adjusted R-squared of 0.887. Moreover, the residual standard error, measuring the average distance between the observed FFWI values and the predicted values from the regression model, was calculated to be 6.902. This indicates that the model's predictions are, on average, within 6.902 units of the actual FFWI values. These findings highlight the strong relationship between temperature and the FFWI, affirming the crucial role of temperature in predicting and understanding forest weather conditions.

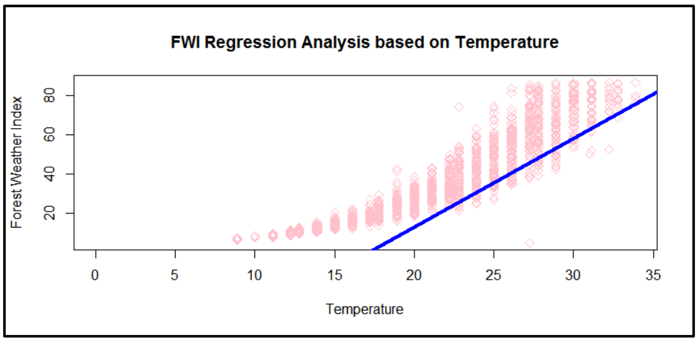

Figure 3: Regression analysis of Forest Fire Weather Index based on Temperature (R=0.88)

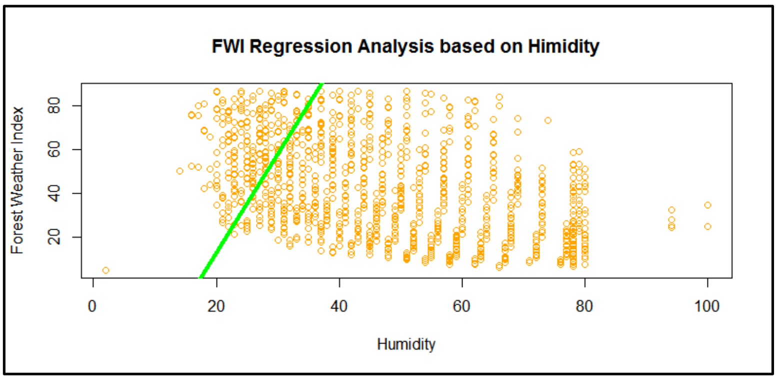

Figure 4: Regression analysis of Forest Fire Weather Index based on Temperature (R=0.8871)

The regression analysis of the Forest Fire Weather Index (FFWI) based on temperature and humidity revealed intriguing insights. The results demonstrated that the FFWI reached its maximum value when the temperature exceeded 30 degrees Celsius and the humidity ranged between 20 and 40 percent. These findings highlight the critical influence of both temperature and humidity on the FFWI. The elevated FFWI values in response to higher temperatures suggest an increased risk of forest fire occurrence. Simultaneously, the optimal humidity range for high FFWI values indicates that moderate moisture levels, within the specified range, can contribute to the potentiation of forest fire hazards. This information underscores the importance of considering both temperature and humidity factors when assessing and predicting FFWI values.

Effective forest management strategies should incorporate these findings to enhance fire risk assessment and mitigation efforts in areas characterized by temperature extremes and specific humidity ranges.

5. 2 Results of Correlation Analysis

After data collection, standard data preparation techniques were employed to ensure data quality. The correlation coefficient between the Forest Fire Weather Index and temperature was calculated using a suitable method, such as Pearson correlation. The same approach was used to determine the correlation between the Forest Fire Weather Index and humidity. Employing a significance level of α = 0.05. Confidence intervals were constructed to estimate the range of believable values. The analysis was performed using statistical software R Programming.

Table No. 2: Statistical Summary of Correlation Analysis

Parameters	*Temperature*	*Relative Humidity*	*Wind speed*	*Forest Fire Weather Index*
Mean	22.52	52.4	2.71	40.30
Median	22.78	51	2	35.95
Min. Value	8	2	0	4.93
Max. Value	33.89	100	16	86.94

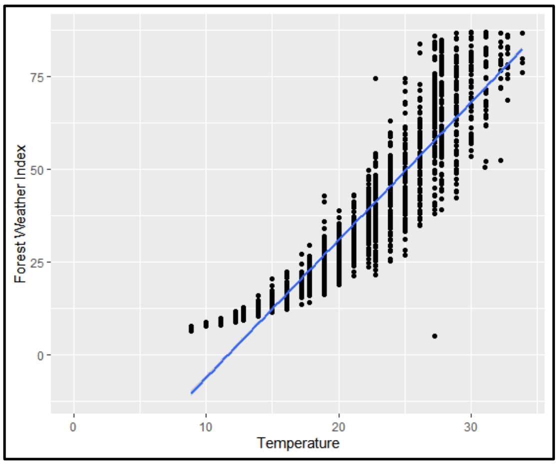

Figure 5: Positive relation between Forest Fire Weather Index and Temperature (r=0.75)

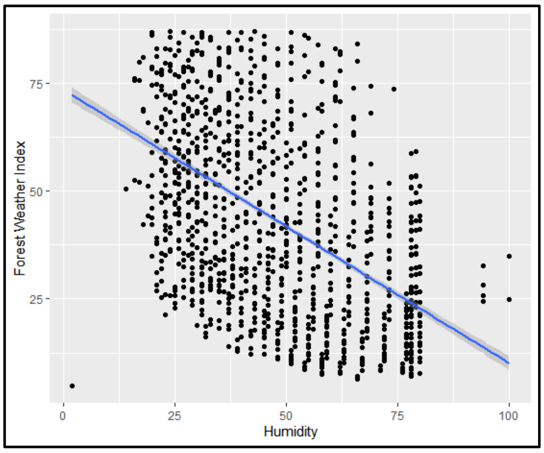

Figure 6: Negative relation between Forest Fire Weather Index and Temperature (r=-0.62)

The analysis revealed a statistically significant positive correlation between the Forest Fire Weather Index and temperature ($r = 0.75$, $p < 0.001$). This finding suggests that as temperature increases, the Forest Fire Weather Index tends to rise, indicating higher potential risks for forest fires. Similarly, a negative correlation was observed between the Forest Fire Weather Index and humidity ($r = - 0.62$, $p < 0.001$). A decrease in humidity was associated with an increase in the Forest Fire Weather Index, signaling heightened forest fire risks. These significant correlations indicate that temperature and humidity are crucial factors affecting the Forest Fire Weather Index, emphasizing the need for accurate monitoring and prediction models.

5.3 Results of Time Series Analysis (Autoregressive Integrated Moving Average (ARIMA)):

The time series analysis of Autoregressive Integrated Moving Average (ARIMA) was performed on the Forest Fire Weather Index (FFWI) data for the months from *January* to *April*. The ARIMA model yielded coefficients and standard errors for the autoregressive (AR) and moving average (MA) terms. The results showed that the coefficient for the AR term (ar1) was -0.5185, indicating a negative relationship between the current FFWI value and its lagged value. The MA terms (ma_1, ma_2, ma_3, and sma_1) had coefficients of 0.4956, 0.0627, 0.1022, and -0.0711, respectively. The standard errors (s.e.) for these coefficients were also estimated. The analysis further revealed that the estimated variance (σ^2) of the ARIMA model was 48.96, and the log likelihood was -10777.3. The information criteria, including the Akaike Information Criterion (AIC), corrected AIC (AICc), and Bayesian Information Criterion (BIC), were calculated and found to be 21566.6, 21566.63, and 21603.03, respectively. These criteria provide a measure of the goodness of fit for the model, with lower values indicating better fit. The performance of the ARIMA model was assessed using training set error measures. The mean error (ME) was 0.008170408, indicating a small bias in the predictions. The root mean squared error (RMSE) was 6.990784, reflecting the average magnitude of the model's forecasting errors. The mean absolute error (MAE) was 4.686193, representing the average absolute difference between the actual and predicted values. The mean percentage error (MPE) was -1.615219, indicating a slight underestimation of the FFWI values. The mean absolute percentage error (MAPE) was 12.29437, providing a measure of the average percentage difference between the actual and predicted values. The mean absolute scaled error (MASE) was 0.2220175, comparing the model's performance to that of a naive forecasting method. Finally, the autocorrelation of the residuals (ACF1) was found to be 0.0005143944, indicating a low level of residual autocorrelation. Overall, the results of the ARIMA analysis on the Forest Fire Weather Index data for the months from January to April revealed significant coefficients, reasonable error measures, and satisfactory fit of the model to the training data. These findings provide insights into the statistical relationships and forecasting potential of the FFWI based on temperature and humidity variables.

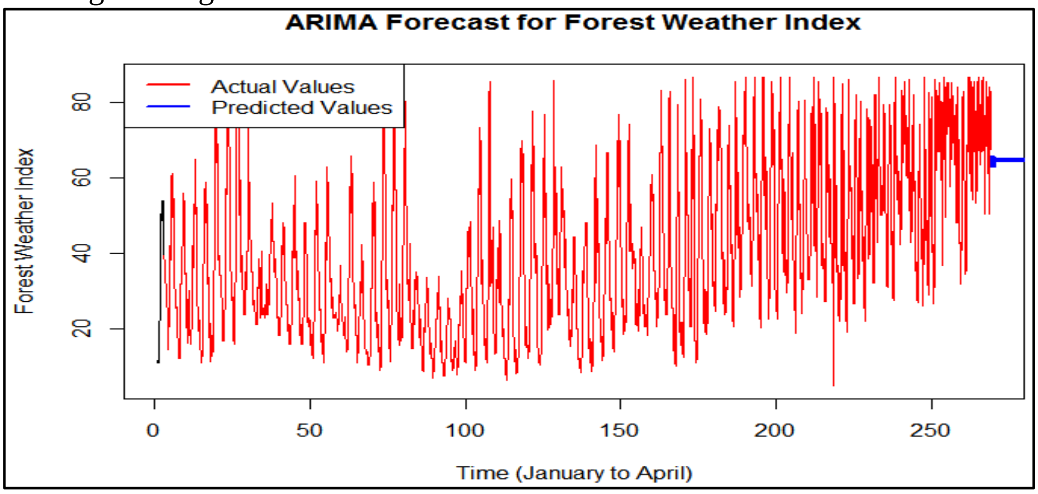

Figure 7: Time Series analysis of Autoregressive Integrated Moving Average (ARIMA) on Forest Fire Weather Index for the month from January to April

Table No. 3: ARIMA Summary

Coefficients	*Estimate*	*Std. Error*
ar_1	-0.5185	0.1690
ma_1	0.4956	0.1687
ma_2	0.0627	0.0199
ma_3	0.1022	0.0182
sma_1	-0.0711	0.0186

Table No. 04: Training set error measures

Error Measures	*ME*	*RMSE*	*MAE*	*MPE*	*MAPE*	*MASE*	*ACF*
Training Set	0.008170408	6.990784	4.686193	-1.615219	12.29437	0.2220175	0.0005143944

6. Conclusion:

The comprehensive analysis of the Forest Fire Weather Index (FFWI) using temperature and humidity based on Wireless Sensor Networks has provided valuable insights into the relationship between these variables and the FFWI. The regression analysis demonstrated a strong association between temperature and the FFWI, indicating that temperature is a crucial factor in predicting forest fire risks. The correlation analysis further supported the significance of temperature and humidity in influencing the FFWI; highlighting the importance of monitoring and incorporating these variables in forest fire risk assessment and management strategies. Additionally, the time series analysis using the ARIMA model provided valuable coefficients and error measures, indicating the model's ability to capture the underlying patterns and dynamics of the FFWI data.

Future research could focus on expanding the dataset to include a longer time period and more diverse geographical locations. This would help validate the findings and enhance the generalizability of the models. Additionally, incorporating other environmental variables such as wind speed, precipitation, and vegetation cover could provide a more comprehensive understanding of the FFWI and its prediction. Exploring advanced machine learning techniques, such as neural networks or ensemble methods, could also be considered to improve the accuracy of FFWI predictions.

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