142. Jahrgang (2025), Heft 1, S. 1–38

Austrian Journal of Forest Science
Centralblatt für das gesamte Forstwesen

Comparative Analysis of Linear Regression and Machine Learning Models for Dead Fuel Moisture Content Prediction in Golestan Province Forests in northeast Iran

Vergleichende Analyse linearer Regressions- und maschineller Lernmodelle zur Vorhersage des Feuchtigkeitsgehalts von totem Brennmaterial in den Wäldern der Provinz Golestan im Nordosten des Iran

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Keywords: Environmental variables, fine fuel, deadwood, Regression model, SVM, RF, CNN, Wildfire risk

Schlüsselbegriffe: Umweltvariablen, Brennmaterial, Totholz, Regressionsmodell, SVM, RF, CNN, FMC, Waldbrandrisiko

Abstract

Accurate prediction of dead fuel moisture content (FMC) is critical for wildfire management, particularly in the Hyrcanian forests of Iran. This study evaluates the performance of machine learning models—Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GBoost), and Convolutional Neural Network (CNN) versus traditional linear regression methods in predicting FMC for three fuel classes (1-hr, 10-hr, and litter) over Golestan province, NE Iran. Using data collected from 235 plots between March and November 2023, we incorporated meteorological variables including temperature (T), relative humidity (RH), and wind speed (WS), along with topographic features, into the models. The results showed that multivariable

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models considerably outperformed the univariate models, and machine learning models were more accurate than the linear regression models. The most accurate model was RF reaching an adjusted coefficient of determination (R^2_{adj}) of 97.08 and a relative RMSE of 5.93%, considering the training data. Meanwhile, with the test data, RF obtained an R^2_{adj} of 87.99, with a relative RMSE of 10.44%. Furthermore, the performance of the SVMs is very good, with an R^2_{adj} of 85.40 for the training data and 86.86 for the test data. In contrast, the linear regression models had lower accuracy, with the best performance, from univariate models being RH with a R^2_{adj} of 66.70 and a relative RMSE of 18.90%. Multivariable regression models combining RH, T and vapor pressure deficit (VPD) improved their performance, but still fell short of machine learning models. The results show that RH and VPD were the most important variables for FMC prediction, especially for fine fuels. The machine learning models showed excellent performance due to their capabilities for describing nonlinear relationships and performing well with high-dimensional data enhancing FMC predictions by up to 31% over traditional methods. This study advances the understanding of FMC dynamics by demonstrating the enhanced accuracy of machine learning models in FMC prediction, here studied for complex temperate forest ecosystems. By highlighting the importance of RH and VPD as critical predictors, the findings contribute to the growing body of knowledge on wildfire risk assessment. Still these results underscore the need for further research to refine models and explore their applicability in diverse environments and under varying climatic conditions.

Zusammenfassung

Die genaue Vorhersage des Feuchtigkeitsgehalts totem Brennmaterial (Fuel Moisture Content, FMC) ist entscheidend für das Wildfeuermanagement, insbesondere in den Hyrkanischen Wäldern Irans. Diese Studie bewertet die Leistung von maschinellen Lernmodellen – Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GBoost) und Convolutional Neural Network (CNN) – im Vergleich zu traditionellen linearen Regressionsmethoden bei der Vorhersage des FMC für drei Brennmaterialklassen (1-Stunde, 10-Stunde und Streu) in der Provinz Golestan, Nordost-Iran. Die Daten wurden zwischen März und November 2023 auf 235 Probeflächen erhoben und umfassten meteorologische Variablen wie Temperatur, relative Luftfeuchtigkeit (RH) und Windgeschwindigkeit sowie topografische Merkmale. Die Ergebnisse zeigten, dass multivariable Modelle die univariaten Modelle deutlich übertreffen hinsichtlich Genauigkeit und maschinelle Lernmodelle genauer sind als lineare Regressionsmodelle. Das RF-Modell erreichte die höchste Genauigkeit mit einem adjustierten Bestimmtheitsmaß (R^2_{adj}) von 97,08 und einem relativen RMSE von 5,93 % für die Trainingsdaten. Für die Testdaten erzielte RF ein adjustiertes R^2 von 87,99 und einen relativen RMSE von 10,44 %. Auch SVM zeigte eine sehr gute Leistung mit einem adjustierten R^2_{adj} von 85,40 für die Trainingsdaten und 86,86 für die Testdaten. Im Gegensatz dazu wiesen lineare Regressionsmodelle eine deutlich geringere Genauigkeit

auf. Das beste univariate Modell, basierend auf RH, erreichte ein adjustiertes R^2_{adj} von 66,70 und einen relativen RMSE von 18,90 %. Multivariable Regressionsmodelle, die RH, Temperatur und VPD kombinierten, verbesserten die Leistung, blieben jedoch hinter den maschinellen Lernmodellen zurück. Die Ergebnisse verdeutlichen, dass RH und VPD die wichtigsten Variablen für die FMC-Vorhersage sind, insbesondere für feines Brennmaterial. Die ausgezeichnete Leistung der maschinellen Lernmodelle ist auf ihre Fähigkeit zurückzuführen, nichtlineare Zusammenhänge zu erfassen und mit hochdimensionalen Daten effektiv umzugehen. Diese Modelle verbesserten die Vorhersagegenauigkeit des FMC um bis zu 31 % im Vergleich zu traditionellen Methoden. Diese Studie erweitert das Verständnis der Dynamik von FMC in Brennmaterial, indem sie die verbesserte Genauigkeit maschineller Lernmodelle bei der FMC-Vorhersage aufzeigt, insbesondere in komplexen gemäßigten Waldökosystemen. Durch die Hervorhebung der Bedeutung von RH und VPD als kritische Prädiktoren tragen die Ergebnisse zur wachsenden Wissensbasis für die Bewertung von Waldbrandrisiken bei. Dennoch unterstreichen diese Ergebnisse die Notwendigkeit weiterer Forschung, um die Modelle zu verfeinern und ihre Anwendbarkeit in unterschiedlichen Umgebungen und unter verschiedenen klimatischen Bedingungen zu untersuchen.

1 Introduction

The fuel moisture content (FMC) is a critical factor influencing wildfire behavior and management (Lewis *et al*., 2024). Accurate prediction of FMC helps mitigate the adverse impacts of wildfires by improving preparedness and response strategies (Hou *et al*., 2024). As such, it is included in most wildfire behavior and effects models. Broadly, previous studies have shown that FMC has a significant impact on ignition, the rate of spread (ROS), radiation efficiency, and energy release, which are essential for accurately assessing wildfire risk (Bilgili *et al*., 2019; Lee *et al*., 2020; Fan *et al*., 2023; Hou *et al*., 2024). When fuel is moist, its water content must evaporate before ignition, requiring more energy to sustain combustion and making it harder for fires to start, spread, or consume fuel (Nelson, 2001).

Traditionally, FMC prediction has relied on empirical models considering meteorological and topographical variables (Kane and Prat-Guitart, 2018). In this regard, models of fuel moisture levels based on various weather conditions have been developed using empirical, semiphysical, or physical methods (Carlson *et al*., 2007; Matthews, 2010; Nelson, 2001; Rodrigues *et al*., 2024; Sharples *et al*., 2009). Moreover, Viney (1991), Nelson (2001), and Aguado *et al*. (2007) demonstrated the importance of relative humidity and temperature in Mediterranean regions. Zhou and Vacik (2017) also conducted an investigation into fuel stick moisture in coniferous forests of eastern Austria, revealing that fuel moisture content is heavily influenced by forest canopy structure, weather conditions, and seasonal variations. Masinda *et al*. (2021) developed models for predicting the Fine Fuel Moisture Code (FFMC) using meteorological and soil variables for *Pinus koraiensis*, *Pinus sylvestris*, and *Larix gmelinii* fuels. This study showed that temperature, relative humidity, and rainfall were the main drivers affecting FMC values (Masinda *et al*., 2021). However, these models often have limitations in handling complex, nonlinear relationships among variables. With their increasing use in modeling complex, nonlinear relationships between independent and dependent variables, machine learning algorithms are not just theoretical concepts. They are frequently applied as both process and statistical models, and their practical applications are becoming increasingly evident (Capps *et al*., 2022; Xu *et al*., 2024; Hou *et al*., 2024; Lyell *et al*., 2024). Recently, these methods have gained significant attention in various fields, including the prediction of FMC (Jain *et al*., 2020; Hou *et al*., 2024). For example, Fan *et al*. (2023) employed a machine learning-based approach to predict dynamic changes in FMC for typical dead surface fuels in the cold temperate region of Northeast China by comparing the results with those of traditional equilibrium moisture content models. Similarly, Miller *et al*. (2023) developed a temporal convolutional network to estimate surface FMC across the continental United States. Capps *et al*. (2022) used a Random Forest (RF) model to estimate FMC in California. Common machine learning models employed for FMC prediction include RF, support vector machine (SVM), and gradient boosting (GBoost) models. All of these models have strengths and limitations. For instance, linear regression is straightforward and interpretable but is best suited for linear relationships; although computationally efficient, linear regression struggles with nonlinearities and is sensitive to outliers (Jain *et al*., 2020). RF, which uses decision trees to mitigate overfitting, handles high-dimensional data well and can assess feature importance. However, this approach sacrifices interpretability and presents challenges in parameter tuning (Lee *et al*., 2020). SVMs, on the other hand, are adept at handling nonlinear problems through the use of various kernel functions, but selecting the appropriate kernel and parameters can be computationally expensive, especially with large datasets (Noble, 2006). While these models are widely used individually for FMC prediction, the need for more comprehensive comparisons across different models is pressing. The current limitations in this area make it difficult to fully assess how their predictive capabilities vary under different conditions, highlighting the urgency of further research in this field.

RF and SVM are among the most popular algorithms that have been implemented. RF is an ensemble learning method that has been demonstrated to handle large datasets with numerous variables effectively, providing robust predictions even in the presence of noise and collinearity (Breiman, 2001). In recent decades, the Hyrcanian temperate forest region in Northern Iran, particularly in Golestan Province, has been severely affected by wildfires (Jahdi *et al*., 2023; Alhaj Khalaf *et al*., 2024). However, to date, no comprehensive studies have applied advanced FMC modeling techniques to the Hyrcanian forests of Northern Iran. These forests, with their unique climatic and topographical characteristics, present specific challenges for wildfire prediction. This study builds on the available literature to address this gap by conducting a comprehensive analysis of regression and machine learning models and comparing their performance in predicting FMC for different time lag classes. By identifying the most effective parameters and modeling approaches, this research aims to contribute to the development of more accurate and reliable FMC prediction tools for wildfire management in the temperate forest ecosystems of Iran. We hypothesize that machine learning models, with their ability to capture nonlinear interactions, will outperform traditional methods and provide more accurate predictions

2 Materials and methods

2.1 Study area

This study was conducted in Golestan Province, NE Iran (30° 36' to 38° 08' N, 53° 51' to 56° 19' E), which has an area of 20,367 km² (Figure1). Topographically, the area ranges in elevation from several meters below mean sea level to approximately 3800 m above mean sea level, which parts of the eastern Alborz Mountain Range stretch from west to east of the Golestan Province.

The mean annual temperature in the study area is 16.88 °C, and the mean annual precipitation is 454 mm. The study area is characterized by diverse land uses, with forest and rangeland dominating the southern and southeastern areas. These forests are primarily composed of broadleaf deciduous species such as hornbeam (*Carpinus betulus* L.), Caucasian oak (*Quercus castaneifolia* C.A.Mey.), Oriental beech (*Fagus orientalis* Lipsky.), Caucasian alder (*Alnus subcordata* C.A.Mey.), velvet maple (*Acer velutinum* Boiss.), Caspian honey locust (*Gleditsia caspica* Desf.), Wych elm (*Ulmus glabra* Huds.), lime (*Tilia begonifolia* Stev.), and Persian ironwood (*Parrotia persica* C.A. Meyer). In contrast, the northern and northeastern parts of the study area consist of bare ground and agricultural land, where crops like wheat, barley, and rice are cultivated. Sparse vegetation and degraded rangelands are common due to intensive agriculture activities and grazing pressures. Additionally, valuable species such as Caspian Hyrcanian English yew (*Taxus baccata* L.), Mediterranean cypress (*Cupressus sempervirens* var. horizontalis), boxwood (*Buxus hyrcana* Pojark.), and Caucasian elm (*Zelkova carpinifolia* Pall.) are considered genetic reserves of the province, emphasizing the ecological significance of conserving these species and the ecosystems they inhabit.

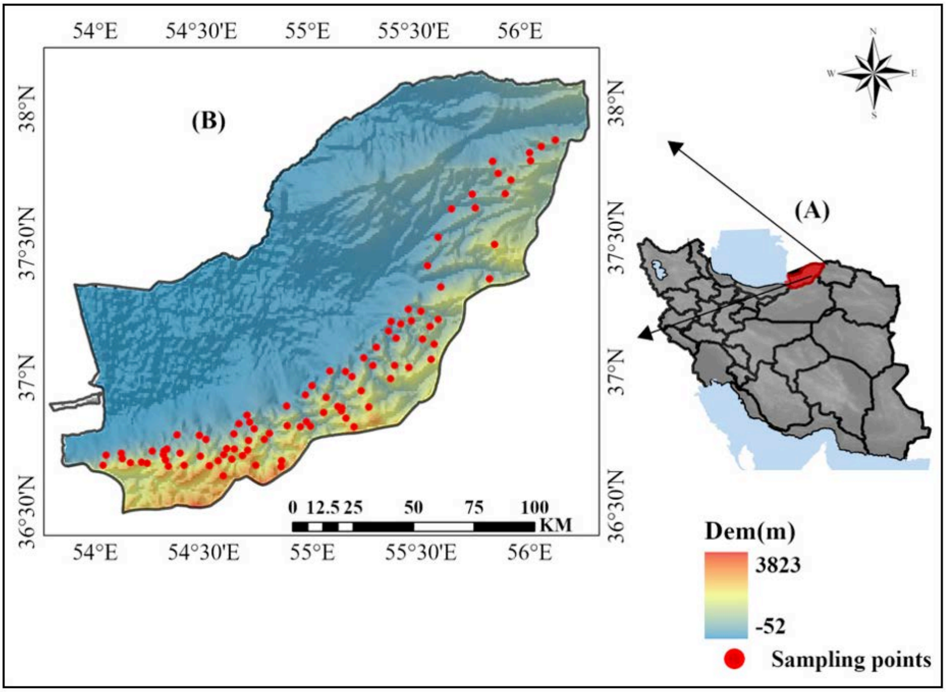

Figure 1: Location of Golestan Province in Iran (A), and digital elevation model of the study area with the locations of the sampling points (B).

Abbildung 1: Lage der Provinz Golestan im Iran (A) und digitales Höhenmodell des Untersuchungsgebiets mit den Standorten der Probepunkte (B).

2.2 Field sampling

The three fuel classes (1-hr, 10-hr, and litter) used for this study are distinguished by size and moisture response time (Figure 2). 1-hr fuels consist of small twigs less than 6 mm in diameter, which respond to moisture changes within about one hour, making them highly flammable and essential for rapid fire ignition and spread. 10-hr fuels include slightly larger twigs and branches, ranging from 6 to 25 mm in diameter, and they take about 10 hours to adjust to moisture changes, playing a key role in sustaining fire spread after ignition. Litter fuels composed of fallen leaves, needles, and fine organic matter on the forest floor, mostly from dominant tree species such as *Quercus castaneifolia* and *Fagus orientalis*, form an often continuous fuel bed maintaining surface fire spread, particularly in forested areas. These fuel classes influence critical fire behavior characteristics, including ignition potential, rate of spread, and fire intensity, which are pivotal for wildfire risk assessment and management due to their varying flammability and moisture retention characteristics. The sampling period from March to November 2023 was chosen to capture seasonal variations in FMC, aligning with the fire seasons in Golestan Province (Alhaj Khalaf *et al*., 2022). We collected samples on 235 plots. Within each plot, various parameters, including fuel load for 1-hr and 10-hr and litter class, were measured via field surveys and the cluster sampling method to ensure spatial representation across the study area, considering variability in topography, vegetation, and metrological characteristics, as outlined by the Forest Health Monitoring (FHM) method (USDA Forest Service, 2005, 2020). In this method, each plot featured three fuel transects radiating from the center at 30, 150, and 250 degrees. The angles (30°, 150°, and 250°) were selected to ensure even spatial coverage within each plot, minimizing sampling bias. This approach follows standard procedures outlined in the FHM methodology. A 1 m × 1 m square subplot was placed along each transect to collect samples. These samples were weighed using a balance with a precision of 0.01 grams. Additionally, meteorological parameters were measured using portable devices placed at the center of each plot during sampling. These data, coupled with records from 60 meteorological stations processed using the meteoland package (v2.1.0) in R, were utilized to estimate daily dead fuel moisture content. The measured meteorological data were used to estimate actual dead fuel moisture content values and to validate machine learning models. These field measurements were critical for estimation fine-scale FMC values, while interpolated data from meteorological stations allowed for broader spatial and temporal analysis. The topographic wetness index (TWI) was also calculated based on the digital elevation model (DEM) in ArcGIS (10.8.1) (Eq.1).

$$TWI = \ln\left(\frac{a}{\tan(b)}\right) \qquad \text{(Eq. 1)}$$

a is Specific Catchment, derived from flow accumulation and *b* is slope (in radians), indicating terrain steepness.

The FMC quantifies the water content in the sample by calculating the ratio of the difference between the wet mass (w_0) and the dry mass (w_{dry}), as described by Norum (1984), using the following equation. Where dry mass was determined using the oven-drying method. For 1-hr and 10-hr fuels, samples were dried at 105°C for 24 hours to ensure complete moisture evaporation, following standard protocols (Matthews, 2010). Litter samples were dried at a lower temperature of 80°C for 48 hours.

$$\mathrm{FMC} = \frac{\mathrm{w_0} - \mathrm{w_{dry}}}{\mathrm{w_{dry}}} * 100 \qquad \text{(Eq. 2)}$$

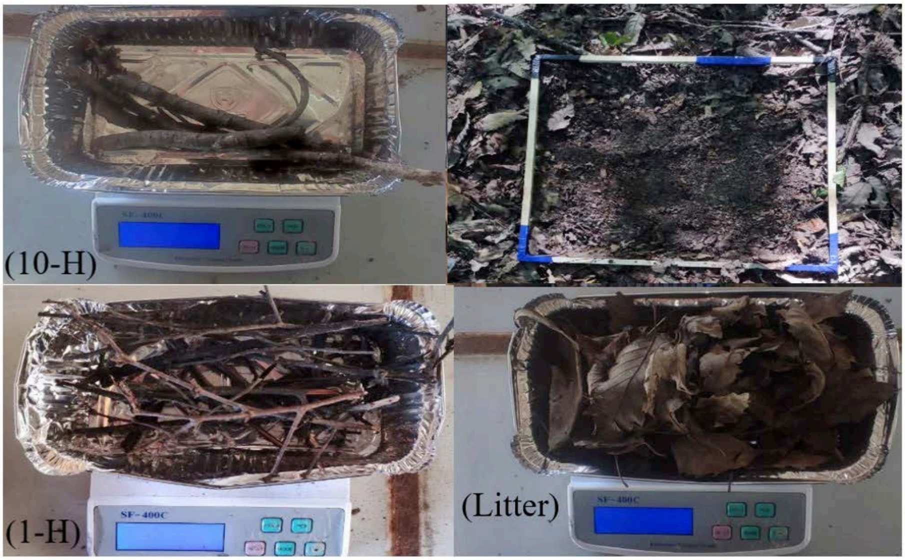

Figure 2: The fuel classess (1-hr, 10-hr, and litter) and the fuel sampling frame used for this study.

Abbildung 2: Die in dieser Studie verwendeten Brennmaterialtypen (1-Stunde, 10-Stunde und Streu) und der Messrahmen.

2.3 Fuel moisture content (FMC) models

Linear regression and machine learning models were used separately to predict FMC. Previous studies have applied these models and found them to be highly accurate at predicting FFMC (Alves *et al*., 2009; Lee *et al*., 2020; Masinda *et al*., 2021; Matthews, 2006; Zhao, 2022). In this study, 70% of the data were used to train the models, while the remaining 30% were used to test and compare their performance. Models were constructed using the Caret, RandomForest, Keras, and XSboost packages in RStudio. Each model is described below.

2.4 Linear regression model

To model the relationship between meteorological variables and fuel moisture, several different approaches and equations have been tested (Eqs 3-16).

$$FMC = b0 + b1 * T \quad \text{(Eq. 3)}$$

$$FMC = b0 + b1 * RH \quad \text{(Eq. 4)}$$

$$FMC = b0 + b1 * W \quad \text{(Eq. 5)}$$

$$FMC = b0 + b1 * CC \quad \text{(Eq. 6)}$$

$$FMC = b0 + b1 * FMC.S \quad \text{(Eq. 7)}$$

$$FMC = b0 + b1 * VPD \quad \text{(Eq. 8)}$$

$$FMC = b0 + b1 * TWI \quad \text{(Eq. 9)}$$

$$FMC = b0 + b1T + b2RH \quad \text{(Eq. 10)}$$

$$FMC = b0 + b1T + b2RH + b3 * WS \quad \text{(Eq. 11)}$$

$$FMC = b0 + b1T + b2RH + b3 * CC \quad \text{(Eq. 12)}$$

$$FMC = b0 + b1T + b2RH + b3 * FMC.S \quad \text{(Eq. 13)}$$

$$FMC = b0 + b1T + b2RH + b3 * VPD \quad \text{(Eq. 14)}$$

$$FMC = b0 + b1T + b2RH + b3 * TWI \quad \text{(Eq. 15)}$$

$$FMC = b0 + b1T + b2RH + b3WS +$$

$$b4CC + b5FMC.S + b6VPD + b7 * TWI \quad \text{(Eq. 16)}$$

where *FMC* is the fuel moisture content, T is the air temperature (°C), *RH* is the air relative humidity (%), *WS* is the wind speed (m/s), *Ln* is the natural logarithm, and *b0*, *b1*, *b2*, and *b3* are the regression coefficients to be estimated.

2.5 Machine learning models

This study applied several machine learning models: Random Forest (RF), support vector machine (SVM), gradient boosting (GBoost), and convolutional neural network (CNN) models. They are designed to handle complex, nonlinear relationships found in high-dimensional data, making them ideal for predicting FMC (Fan *et al.*, 2023).

2.5.1 Random Forest (RF)

RF is a method of ensemble learning based on decision-making. The method constructs and merges many decision trees for a more accurate and stable prediction (Alavi *et al*., 2017). The RF algorithm works well on large datasets with many variables and yields strong predictions even in the case of noisy data with collinearity. The high predictive accuracy of RF makes it excel at dealing with complex nonlinear interactions across different factors and dimensions. In contrast, the training time is faster. For example, with methods such as bagging and boosting, RF is highly resilient to outliers and noise and ensures robust performance. RF has been widely used to predict fine FMCs and has presented excellent outcomes in previous studies (Lee *et al*., 2020; Fan and He, 2021; Masinda *et al*., 2021). The RF model was fine-tuned by optimizing the number of trees (ntree) and the number of variables considered at each split (mtry). These parameters were chosen through grid search and cross-validation to ensure the best predictive accuracy. The model's performance was assessed using root mean square error (RMSE) and adjusted R^2 values. A quantitative assessment is performed to test the significance and importance of the independent variables. The RF model for FMC prediction can be written as follows:

$$FMC_{RF} = \left(\frac{1}{N}\right) \sum Tree\_i(x) \qquad \text{(Eq. 17)}$$

where *Tree_i(x)* indicates the *i-th* tree prediction and *N* is the total number of trees in the forest. The final prediction from the RF model is the average of the predictions from all the individual trees.

2.5.2 Support Vector Machines (SVM)

The SVM is a general machine learning algorithm applicable to classification and regression (Jakkula, 2020). SVM is dedicated to finding the best hyperplane that can separate data points within a feature space and then finds an optimal hyperplane that divides the data. Using kernel functions allows SVMs to map the input feature space into a much higher-dimensional space in which more accurate hyperplanes can be identified for the solution of even intricate nonlinear problems. Therefore, the kernel in the study was selected as a radial basis function due to its better performance in wide predictive modeling contexts. Optimizing the hyperplane in SVM is determined by implementing a loss function and penalty mechanism. Numerous studies have shown the ability of SVM models to predict FMC (Fan *et al*., 2023; Lee *et al*., 2020; Rodrigues *et al*., 2024). The FMC prediction model by SVM can be expressed as follows:

$$FMC_{SVM} = \sum \alpha i\, K(xi\ x) + b \qquad \text{(Eq. 18)}$$

where α_i are the parameters of the model, $K_{(xi\ x)}$ is the kernel function, x_i are support vectors of the data, and b is associated with the bias. The kernel function $K_{(xi\ x)}$ determines the similarity of the input vectors.

the radial basis function (RBF) kernel was selected for its effectiveness in capturing nonlinear relationships. The key parameters fine-tuned were the penalty parameter (*C*) and the kernel coefficient (*γ*). This tuning was performed using the Caret package in *R* to balance prediction accuracy and computational efficiency.

2.5.3 Gradient boosting (GBoost)

GBoost is an ensemble learning technique used for regression and classification problems. GBoost models are built by training an ensemble of weak learners, typically decision trees, one per instance. The key feature of GBoost is that new learners are added using a functional approach. Each new learner greedily minimizes a loss function. It incrementally updates the model, giving more attention to instances that were previously misclassified, thereby reducing bias and variance (Shmuel *et al*., 2022). The GBoost algorithm is represented as follows:

$$FMC_{\ GB} = \sum_{m=1}^{m} \gamma m \ \cdot \ hm(x) + \text{const} \qquad \text{(Eq. 19)}$$

where *hm(x)* is the individual weak learner, *γm* is the learning rate, and *m* is the total number of learners. By iteratively optimizing the loss function, GBoost improves the accuracy of FMC predictions. For GBoost, the learning rate (*γ*), the number of trees (*n*), and the maximum depth of each tree (*d*) were optimized using grid search. These parameters control the model's complexity and its ability to generalize.

2.5.4 Convolutional Neural Network (CNN)

A CNN is a deep learning model known to be effective for spatial data and image processing. A CNN uses convolution layers to extract features from input data, which can aid in the study of spatial patterns in FMC (Miller *et al*., 2023). We employed the CNN to forecast FMC using a range of input features. The CNN architecture, designed for stability and reliability, included a 1D convolution layer with 64 filters and a kernel size of 3, followed by batch normalization, flattening, and two fully connected layers with 32 and 16 units. The model was trained with the Adamax optimizer using the root mean square error (RMSE) as the loss function. To mitigate overfitting, we implemented early stopping, which tracked the validation loss, and terminated training when no improvement was observed over 10 consecutive epochs. This strategy enabled the CNN to learn and generalize the relationships between the input features and FMC effectively.

2.6 Model evaluation

To evaluate the performance of linear regression and ML models, several statistical metrics are used as follows:

$$R^2_{adj} = 1 - \left(\frac{(1-R^2)*(n-1)}{n-p-1}\right) \quad \text{(Eq. 20)}$$

$$R^2 = \frac{\sum_{i=1}^{n}(y_i-\hat{y})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad \text{(Eq. 21)}$$

$$RMSE\% = \left(\frac{RMSE}{\bar{y}}\right) * 100 \quad \text{(Eq. 22)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2} \quad \text{(Eq. 23)}$$

$$S_{y.x} = \sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y})^2}{n-p-1}} \quad \text{(Eq. 24)}$$

$$AIC = 2p - 2ln(L) \quad \text{(Eq. 25)}$$

where R^2 and R^2_{adj} are the coefficient of determination and adjusted coefficient of determination, respectively; $\bar{y}$ and $\hat{y}$ are the observed and predicted values, respectively; n and p are the number of observations and number of predictors in the model, respectively; RMSE% is the percentage root mean squared error, normalized by the mean of observed values; $S_{y.x}$ is the standard error of the estimate, measuring the average distance that the data points fall from the fitted regression line; *AIC* is the Akaike information criterion, a measure for model comparison, balancing model fit and complexity; and *L* is the likelihood of the model, measuring how well the model explains the data.

3 Results

The present study used regression and machine learning models to predict FMC for 1-hr and 10-hr timelag classes and litter fuels. More details on the predictive performance of the applied models, the most effective parameters, and comparisons between different modeling approaches are given in the sections below. Table 1 provides a statistical summary of the variables for which the mean FMC values were 16.37, 19.43, and 18.49% for 1-hr, 10-hr, and litter, respectively. The FMC values ranged from 4.20 to 27.75% at 1-hr, from 5.33 to 31.64% at 10-hr, and from 7.68 to 36.56% for litter. Other meteorological parameters, including temperature, precipitation, relative humidity, wind speed, vapor pressure deficit, topographical features (elevation, slope, and topographic wetness index), and canopy cover, were recorded (Table 1).

Table 1: Summary of fuel moisture, canopy cover, fuel load, meteorological, and topographic variables affecting wildfire behavior.

Tabelle 1: Zusammenfassung der Brennmaterial-Feuchtigkeit, Kronenbedeckung, Brennmaterialmenge, meteorologischen und topografischen Variablen, die das Waldbrandverhalten beeinflussen.

Parameter		Mean	Min	Max	Std Dev
FMC (%)	1-hr	16.37	4.20	27.75	5.14
	10-hr	19.43	5.33	31.64	4.95
	Litter	18.49	7.68	36.56	9.23
	Soil	27.85	20.32	33.75	2.54
Canopy cover (%)		63.97	0.00	95.00	25.96
Fuel load (g/m2)	1-hr	382.12	97.61	1628.5	201.5
	10-hr	763.5	32.15	3860.13	493.35
	Litter	1296.26	230.29	4170.6	601.75
Meteorology	Temperature (°C)	19.33	1.60	33.08	8.50
	Precipitation (mm/day)	0.79	0.00	22.48	2.51
	Relative humidity (%)	62.29	37.64	91.23	11.63
	Wind speed (m/s)	3.78	0.74	7.97	1.38
	Vapor Pressure Deficit (Pa)	1029.05	107.34	3961.90	698.85
Topography	Elevation (m)	707.93	131.73	2024.30	452.46
	Slope (degree)	39.98	1.87	359.29	89.78
	Topographic wetness index	3.16	1.08	8.47	1.74

According to the correlation analysis between the different variables determined using the Pearson correlation coefficient (Wackerly, 2008) (Figure 3), for the 1-hr FMC, the highest correlations were observed with relative humidity (RH) and temperature (T). Specifically, RH showed a strong positive correlation (p = 0.82), while temperature exhibited a strong negative correlation (p = -0.68). They also had meaningful correlations for 10-hr, FMC, RH, and temperature. RH was significantly positively correlated (p = 0.83), and temperature was significantly negatively correlated (p = -0.57). The correlations with RH and temperature were slightly weaker for FMC than for 1-hr and 10-hr FMC but still significant. For soil, FMC (FMC. S), highly significant correlations (p = 0.61 and p = 0.44) were observed for RH and temperature, respectively.

There were also notable correlations between the FMCs after 1-hr and 10-hr and between the FMC and litter fuel. The 1-hr and 10-hr FMCs showed a strong positive correlation (p = 0.86). Additionally, strong to moderate positive correlations were found between 10-hr and litter FMC (p = 0.70), between 1-hr and litter FMC (p = 0.83), and between soil FMC and all the other FMCs—1-hr (p = 0.22), 10-hr (p = 0.32), and litter FMC (p = 0.37).

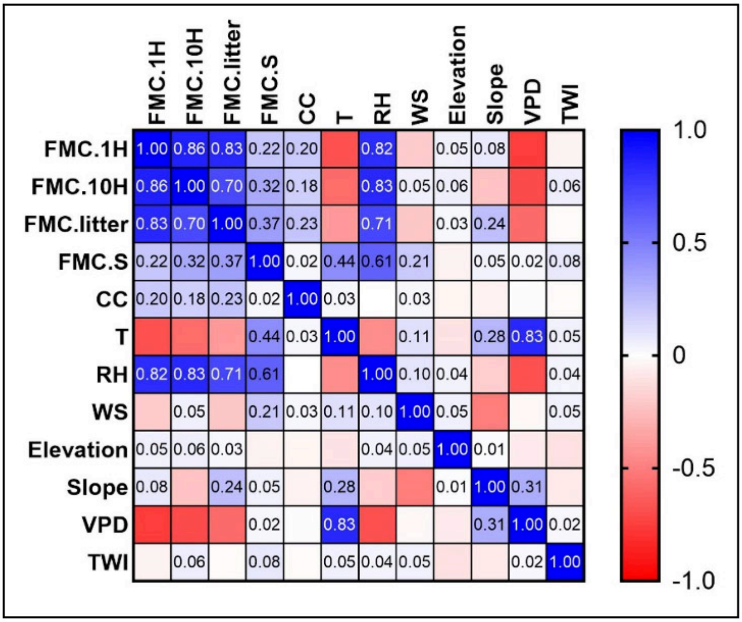

Figure 3: Pearson correlation coefficient between variables affecting FMC.

Abbildung 3: Pearson-Korrelationskoeffizient zwischen den Variablen, die die Brennmaterialfeuchtigkeit (FMC) beeinflussen.

3.1 1-hr FMC

For the prediction of the 1-hr FMC, regression analysis showed that the multivariable models outperformed the single-variable models (Figure 4; Table 2). The multivariable models with temperature (T), relative humidity (RH), wind speed (WS), canopy cover (CC), soil FMC, vapor pressure deficit (VPD), and topographic wetness index (TWI) achieved the highest accuracy (R^2_{adj}= 91, relative RMSE= 9.24%; SY.x= 1.55 for the training data and R^2_{adj}= 83.37, relative RMSE= 13.18%; SY.x= 2.30 for the test data). The multivariable models combining T, RH, and CC also showed improved accuracy, with an R^2_{adj} of 76.61 and an RMSE of 15.45% for the test data. For the single-variable models, the model using RH alone had the highest accuracy (R^2_{adj}= 67.26, relative RMSE= 17.79%, Sy.x= 2.93, and AIC= 356.62 for the training data; R^2_{adj}= 66.70, relative RMSE= 18.90%, Sy.x= 3.14, and AIC= 151.89 for the test data). Conversely, the single-variable model using TWI was the least accurate, with an R^2_{adj} of -1.27, a relative RMSE of 31.58%, and a Sy.x of 5.25 for the test data.

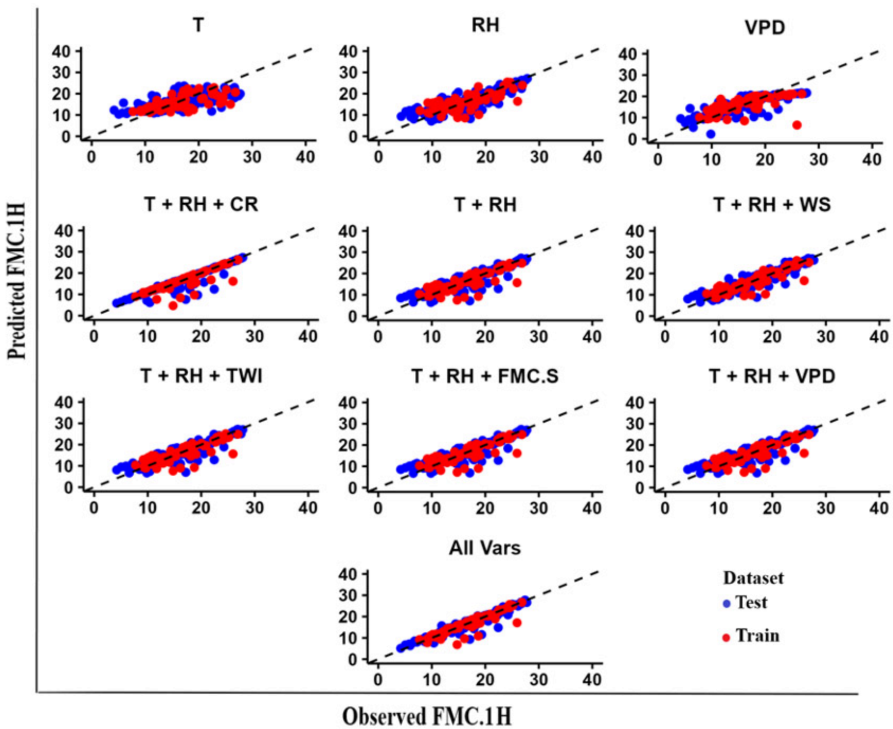

Figure 4: Scatter plot of the predicted and measured values of 1-hr FMC using regression models.

Abbildung 4: Streudiagramm der vorhergesagten und gemessenen Werte der 1-Stunden-FMC unter Verwendung von Regressionsmodellen.

Table 2: 1-hr FMC regression models parameters and accuracy indices.

Tabelle 2: Parameter und Genauigkeitsindizes der Regressionsmodelle für die 1-Stunden- Brennmaterialfeuchtigkeit (FMC).

Model	Coefficients	Train				Test			
		R^2_{adj}	RMSE (%)	Sy.x	AIC	R^2_{adj}	RMSE (%)	Sy.x	AIC
1-hr FMC = b0 + b1*T	b0=24.84; T=-0.439	53.33	21.25	3.50	415.12	27.73	27.26	4.53	204.59
1-hr FMC = b0 + b1*RH	b0=-7.12; RH=0.373	67.26	17.79	2.93	356.62	66.70	18.90	3.14	151.89
1-hr FMC = b0 + b1*W	b0=19.63; WS=-0.873	4.46	30.40	5.00	533.31	1.25	31.32	5.21	225.82
1-hr FMC = b0 + b1*CC	b0=13.968; CC =3.84	3.39	30.57	5.03	535.15	3.33	30.90	5.14	224.38
1-hr FMC = b0 + b1*FMC.S	b0=6.993; FMC.S=0.335	1.88	30.80	5.07	537.72	11.02	30.10	5.01	218.74
1-hr FMC = b0 + b1*VPD	b0=22.653; VPD=-0.006	67.95	17.61	2.90	353.09	34.93	26.74	4.45	197.46
1-hr FMC = b0 + b1*TWI	b0=16.74; TWI=-0.124	-0.46	31.17	5.13	541.60	-1.27	31.58	5.25	227.54
1-hr FMC = b0 + b1*T + b2*RH	b0=3.992; T=-0.263; RH=0.277	82.00	13.15	2.17	258.91	72.45	16.98	2.85	139.01
1-hr FMC = b0 + b1*T + b2*RH + b3*WS	b0=5.286; T=-0.236; RH=0.291; WS=-0.709	85.11	11.93	1.98	228.54	82.19	13.98	2.36	109.35
1-hr FMC = b0 + b1*T + b2*RH + b3*CC	b0=1.364; T=-0.264; RH=0.278; CC =4.143	86.60	11.31	1.87	211.11	76.61	15.45	2.61	127.88
1-hr FMC = b0 + b1*T + b2*RH + b3*FMC.S	b0=-4.196; T=-0.498; RH=0.083; FMC.S=0.893	81.95	13.13	2.17	260.36	71.77	17.16	2.90	140.66
1-hr FMC = b0 + b1*T + b2*RH + b3*VPD	b0=4.729; T=-0.237; RH=0.266; VPD=0.002	81.95	13.13	2.17	260.36	71.77	17.16	2.90	140.66
1-hr FMC = b0 + b1*T + b2*RH + b3*TWI	b0=4.217; T=-0.257; RH=0.282; TWI=-0.21	82.32	13.00	2.15	256.89	72.49	17.10	2.89	138.90
1-hr FMC = b0 + b1*T + b2*RH + b3*WS + b4*CC + b5*FMC.S + b6*VPD + b7*TWI	b0=-17.559; T=-0.814; RH=-0.189; WS=-0.831; CC =4.392; FMC.S=2.225; VPD=0.0015; TWI=-0.121	90.90	9.24	1.55	152.25	83.37	13.18	2.30	104.67

The results obtained for 1-hr FMC using machine learning algorithms are shown in Table 3 and Figures 5,6 where the different machine learning models are tested using all of the variables and the best variables. Among the models, RF had the best general performance, with an R^2_{adj} of 97.4 and a relative RMSE of 5.237% on the training data and 82.7 and 13.891% on the test data when all the variables were used. SVM also performed well, with an R^2_{adj} of 93.3 and a relative RMSE of 8.011% on the training data and 80.9 and 14.422% on the test data. The GBoost model achieved high accuracy during training (R^2_{adj} = 97.6), but significant overfitting was evident, as test performance dropped to R^2_{adj} = 80.1 a relative RMSE of 15.642%. Similarly, the CNN model showed overfitting, with training performance at R^2_{adj} = 94.6 but a reduced test performance of R^2_{adj} = 80.9 and a relative RMSE of 14.45%. In turn, when using the best variables, SVM topped all the models in the test data, with an R^2_{adj} of 84.9 and a relative RMSE of 12.918%, demonstrating the greatest benefit from feature selection. This model benefited more from feature selection than RF but maintained robust performance, with an R^2_{adj} of 82.2 and a relative RMSE of 13.972%.

In general, RH was the most influential parameter across both the regression and machine learning models, significantly enhancing the prediction accuracy. When combined with other variables in multivariable models, temperature, VPD, and CC were also significant, further improving the model performance. The inclusion of the RH improved the prediction performance of the single-variable regression models and further enhanced the prediction performance when RH was combined with temperature, VPD, and CC in the multivariable models.

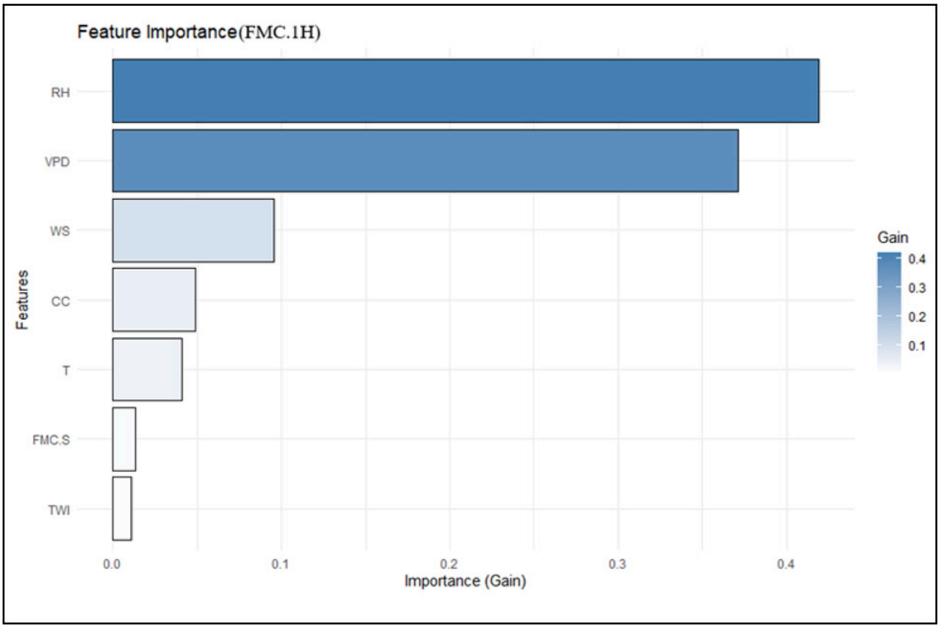

Figure 5: The relative importance of variables in predicting 1-hr FMC using the Gain method.

Abbildung 5: Die relative Bedeutung der Variablen bei der Vorhersage der 1-Stunden-FMC mittels der Gain-Methode.

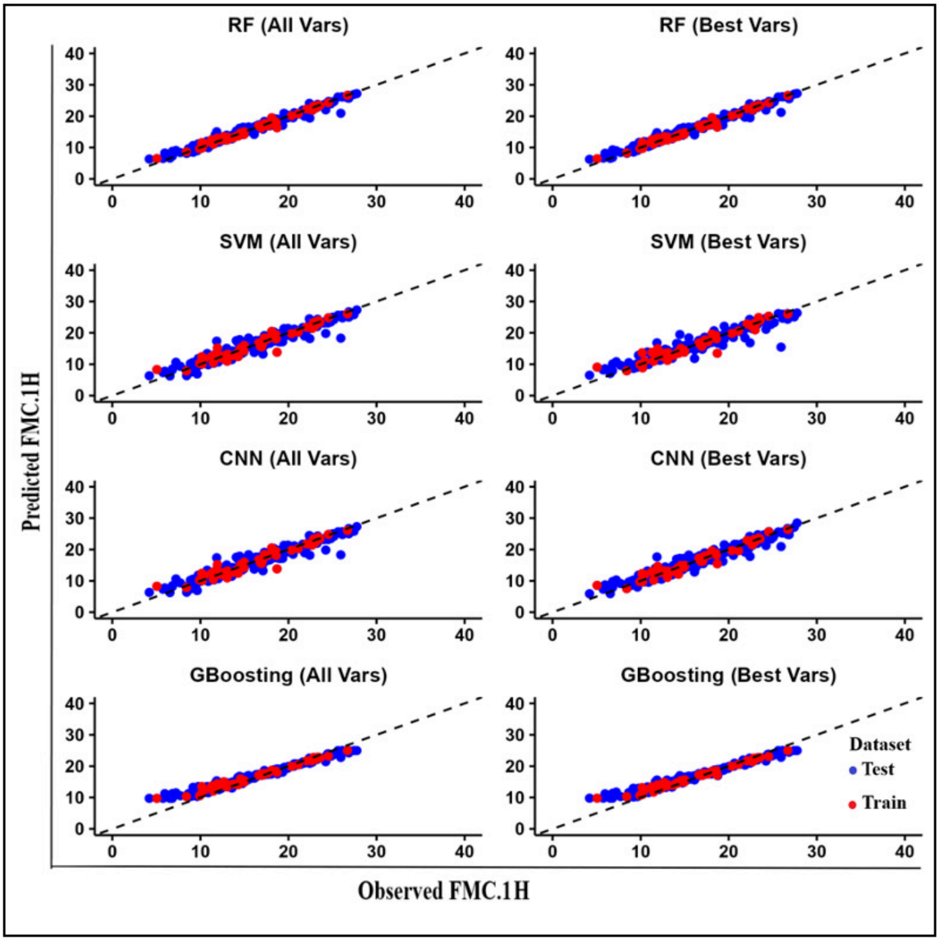

Figure 6: Scatter plot of the predicted and measured values of 1-hr FMC using machine learning models.

Abbildung 6: Streudiagramm der vorhergesagten und gemessenen Werte der 1-Stunden-FMC unter Verwendung von maschinellen Lernmodellen.

Table 3: 1-hr FMC machine learning models accuracy indices.

Tabelle 3: Genauigkeitsindizes der maschinellen Lernmodelle für die 1-Stunden-FMC.

	Model	Train		Test	
		R^2_{adj}	RMSE (%)	R^2_{adj}	RMSE (%)
All variables	RF	97.4	5.237	82.7	13.891
	SVM	93.3	8.011	80.9	14.422
	GBoost	97.6	8.562	80.1	15.642
	CNN	94.6	7.137	80.9	14.45
Best variable	RF	96.4	5.977	82.2	13.972
	SVM	88.9	10.241	84.9	12.918
	GBoost	96.3	9.519	81.7	15.763
	CNN	87.9	10.672	84	13.219

3.2 10-hr FMC

For the prediction of 10-hr FMC, the multivariable models, including T, RH, WS, CC, soil FMC, VPD, and TWI, exhibited high accuracy, with an R^2_{adj} of 74.48 and a relative RMSE of 12.83% for the training data and an R^2_{adj} of 78.69 and a relative RMSE of 11.36% for the test data. The model combining T, RH, and CC also exhibited good performance, with an R^2_{adj} of 84.67 and a relative RMSE of 9.70% for the test data. Among the single-variable models, the RH model was the most accurate (R^2_{adj} = 64.84, relative RMSE= 15.30%, Sy.x= 2.98, AIC= 362.59 for the test data; R^2_{adj} = 77.22, relative RMSE= 11.99%, Sy.x= 2.38, AIC= 113.87 for the training data). The WS model was the least accurate, with an R^2_{adj} of 0.76 and a relative RMSE of 25.71% for the training data and an R^2_{adj} of -0.36 and relative RMSE of 24.72% for the test data (Table 4; Figure 7).

RH, VPD, and 1-hr FMC were the most influential predictors. When RH was included in the multivariable models, the R2adj significantly improved from 77.22 to 84.67 when RH was combined with temperature, VPD, and 1-hr FMC. Among the machine learning models, the combination of these variables allowed RF to achieve an R^2_{adj} of 73.43 and a relative RMSE of 12.51%, while SVM was less effective, with an R^2_{adj} of 49.48 and a relative RMSE of 20.65%. While the 1-hr FMC models showed higher accuracy, both the 1-hr FMC and 10-hr FMC predictions benefited from the use of multiple variables, with RH being the most critical parameter. The machine learning models outperformed the traditional regression models, with RF providing the best performance across both datasets (Table 4).

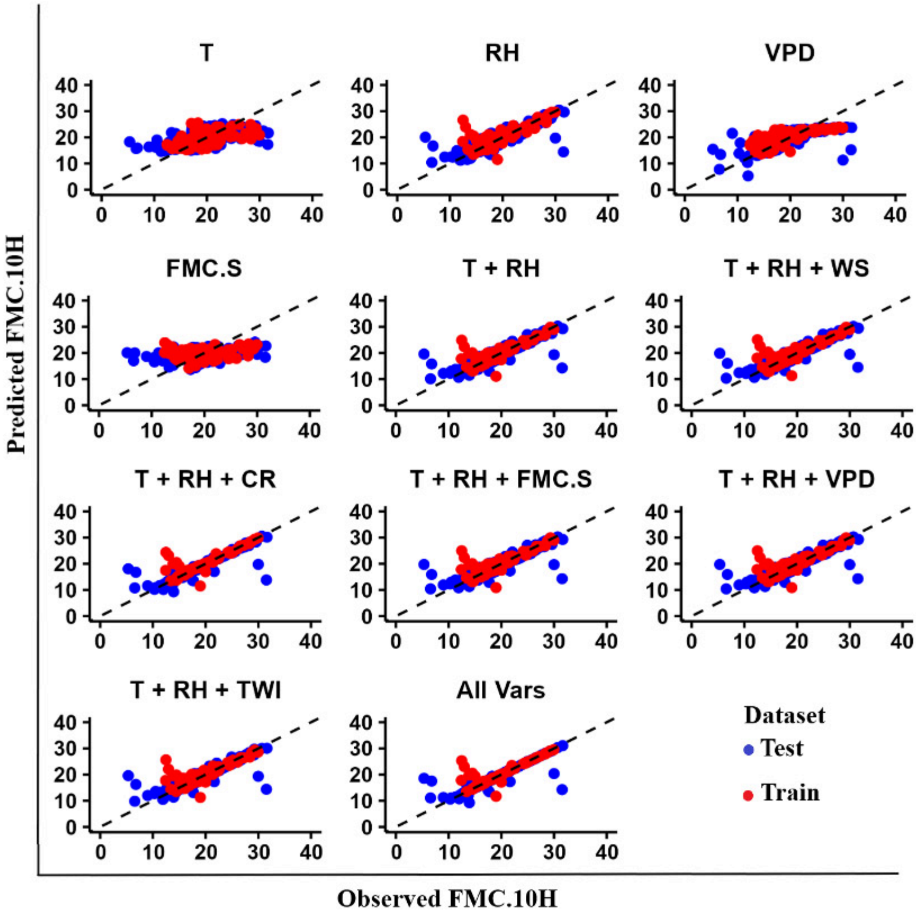

Figure 7: Scatter plot of the predicted and measured values of 10-hr FMC using regression models.

Abbildung 7: Streudiagramm der vorhergesagten und gemessenen Werte der 10-Stunden-FMC unter Verwendung von Regressionsmodellen.

Table 4: 10-hr FMC regression models parameters and accuracy indices.

Tabelle 4: Parameter und Genauigkeitsindizes der Regressionsmodelle für die 10-Stunden-FMC.

Model	Coefficients	Train				Test			
		R^2_{adj}	RMSE (%)	Sy.x	AIC	R^2_{adj}	RMSE (%)	Sy.x	AIC
10-hr FMC= b0 + b1*T	b0= 26.844; T=-0.38	38.23	20.28	3.95	455.60	20.71	22.33	4.43	198.68
10-hr FMC= b0 + b1*RH	b0= -3.301; RH=0.362	77.22	11.99	2.38	362.59	64.84	15.30	2.98	113.87
10-hr FMC= b0 + b1*W	b0= 17.769; WS=0.424	0.76	25.71	5.01	533.83	-0.36	24.72	4.91	214.70
10-hr FMC= b0 + b1*CC	b0= 16.797; CC =3.95	3.29	25.38	4.95	529.55	0.40	24.15	4.80	214.19
10-hr FMC= b0 + b1*FMC.S	b0= 2.426; FMC.S=0.605	7.08	24.87	4.85	522.96	16.46	22.13	4.40	202.23
10-hr FMC= b0 + b1*VPD	b0= 25.208; VPD=-0.006	56.99	16.92	3.30	395.88	33.12	21.04	4.18	187.10
10-hr FMC = b0 + b1*TWI	b0= 18.143; TWI=0.395	1.27	25.64	5.00	532.97	0.89	24.98	4.96	213.85
10-hr FMC= b0 + b1*T + b2*RH	b0= 4.208; T=-0.175; RH=0.297	80.14	10.89	2.18	333.14	70.77	13.91	2.72	104.54
10-hr FMC= b0 + b1*T + b2*RH + b3*WS	b0= 3.835; T=-0.179; RH=0.293; WS=0.187	79.13	11.15	2.25	333.65	70.85	13.85	2.72	107.92
10-hr FMC= b0 + b1*T + b2*RH + b3*CC	b0=2.194; T=-0.177; RH= 0.294; CC =3.518	84.67	9.70	1.96	316.56	73.72	13.15	2.58	86.94
10-hr FMC= b0 + b1*T + b2*RH + b3*FMC.S	b0=-25.051; T=-1.007; RH=-0.392; FMC.S=3.17	75.24	12.26	2.47	330.18	71.45	13.70	2.69	119.54
10-hr FMC= b0 + b1*T + b2*RH + b3*VPD	b0=6.65; T=-0.082; RH=0.257; VPD=-0.002	75.24	12.26	2.47	330.18	71.45	13.70	2.69	119.54
10-hr FMC= b0 + b1*T + b2*RH + b3*TWI	b0=4.13; T=-0.178; RH=0.293; TWI=0.141	79.88	10.90	2.20	333.81	70.82	13.85	2.72	105.43
10-hr FMC= b0 + b1*T + b2*RH + b3*WS + b4*CC + b5*FMC.S + b6*VPD + b7*TWI	b0=-23.266; T=-0.899; RH=-0.307; WS=0.153; CC =3.486; FMC.S=2.716; VPD=0.00021; TWI=0.183	78.69	11.36	2.37	316.59	74.48	12.83	2.55	109.34

Table 5 presents the machine learning outcomes for predicting 10-hr FMC using all the variables and the best variables. Among the models, the best balance regarding performance was provided by the RF model using all the variables, which achieved an R^2_{adj} of 94.5 with a relative RMSE of 6.15% on the training data and an R^2_{adj} of 78.0 with a relative RMSE of 12.76% on the test data. GBoost works best on the training data, with an R^2_{adj} of 95.5, while on the test data, it performs much worse, and its relative

RMSE reaches 16.55%, which indicates overfitting. Low performance was achieved in the training of SVM, but the results were competitive, with an R^2_{adj} of 78.4 and a relative RMSE of 12.92% (Figure 8 and Figure 9). Additionally, the CNN had moderate performance, with an R^2_{adj} of 82.3 for the training data and 72.8 for the test data. The best testing performance was obtained with SVM when considering the best variables, for which an R^2_{adj} of 78.5 and a relative RMSE of 12.5% were obtained; these results were slightly improved from the results obtained using all the variables. However, the RF model did not perform well, with an R^2_{adj} of 73.6 and a relative RMSE of 13.92% on the test data, while GBoost and CNN had lower R^2_{adj} values of 69.0 and 78.1, respectively.

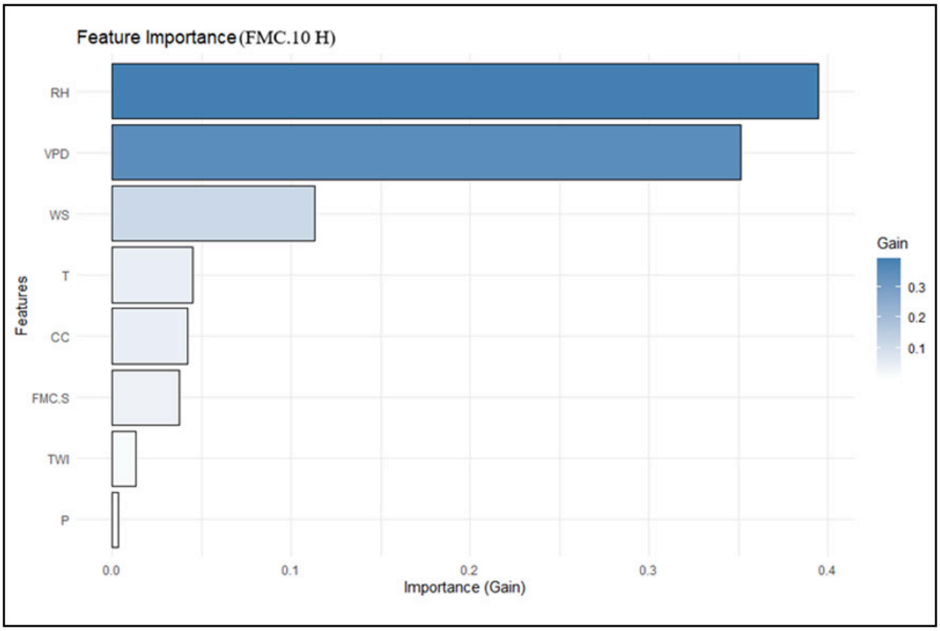

Figure 8: The relative importance of variables in predicting 10-hr FMC using the Gain method.

Abbildung 8: Die relative Bedeutung der Variablen bei der Vorhersage der 10-Stunden-FMC mittels der Gain-Methode.

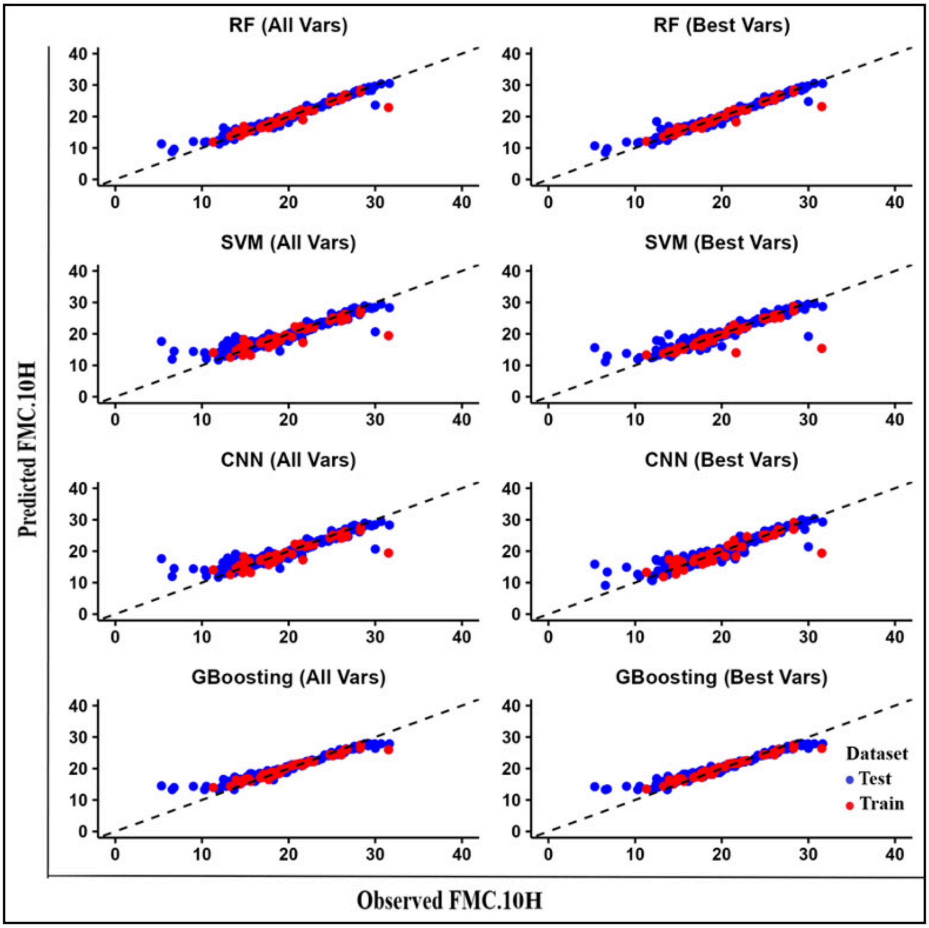

Figure 9: Scatter plot of the predicted and measured values of 10-hr FMC using machine learning models.

Abbildung 9: Streudiagramm der vorhergesagten und gemessenen Werte der 10-Stunden-FMC unter Verwendung von maschinellen Lernmodellen.

Table 5: Accuracy indices of the 10-hr FMC machine learning models.

Tabelle 5: Genauigkeitsindizes der maschinellen Lernmodelle für die 10-Stunden-FMC.

	Model	Train		Test	
		$R2_{adj}$	RMSE (%)	$R2_{adj}$	RMSE (%)
All variables	RF	94.50	6.15	78.00	12.76
	SVM	74.90	12.43	78.40	12.92
	GBoost	95.50	8.13	66.60	16.55
	CNN	82.30	11.10	72.80	14.36
Best variable	RF	94.30	6.19	73.60	13.92
	SVM	81.30	10.70	78.50	12.50
	GBoost	96.20	7.85	69.00	15.78
	CNN	80.10	11.39	78.10	13.18

3.3 Litter FMC

Table 6 presents the results of predicting litter FMC using various regression models, including single- and multiple-variable models. The model incorporated multiple variables, namely, temperature (T), relative humidity (RH), wind speed (WS), canopy cover (CC), and soil FMC (FMC. S), vapor pressure deficit (VPD), and topographic wetness index (TWI) performed the best overall, with an R^2_{adj} of 68.7 and relative RMSE of 14.61% on the training data and an R^2_{adj} of 54.57 and relative RMSE of 15.99% on the test data, indicating strong predictive power when accounting for multiple meteorological and environmental variables.

Among the single-variable models, the RH was the most influential predictor of litter FMC, with an R^2_{adj} of 51.35 and a relative RMSE of 18.51% in the training data and an R^2_{adj} of 46.84 with a relative RMSE of 17.16% in the test data. These results underscore the substantial impact of RH on litter FMC. In comparison, other single-variable models, such as those based on T and WS, exhibited significantly lower predictive power, with R^2_{adj} values less than 20%, highlighting the crucial role of RH in accurately predicting litter FMC.

When T and RH were combined in a two-variable model, a significant improvement in accuracy was observed, achieving an R^2_{adj} of 52.37 on the training data and 45.75 on the test data. Adding WS as a third variable further enhanced the performance, with an R^2_{adj} of 61.61 on the training data and 49.15 on the test data. However, the most accurate predictions were achieved with the full model that included CC and FMC. S, VPD, and TWI, demonstrating substantial progress in predictive accuracy when combining multiple variables (Table 6; Figure 10).

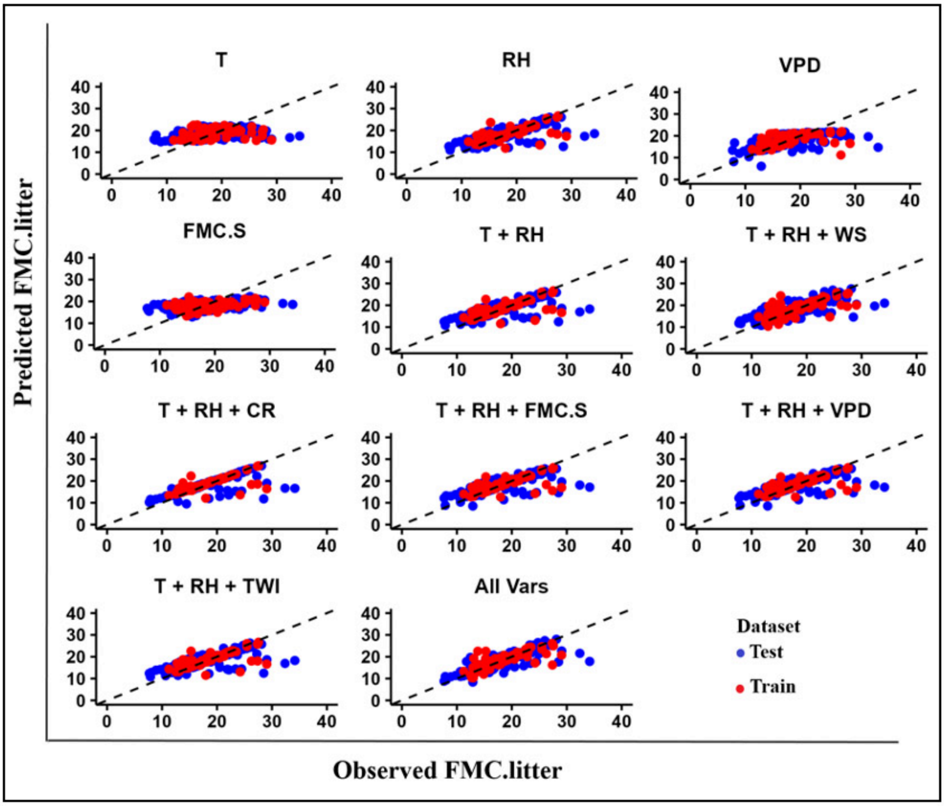

Figure 10: Scatter plot of the predicted and measured values of litter FMC using regression models.

Abbildung 10: Streudiagramm der vorhergesagten und gemessenen Werte der Streu-FMC unter Verwendung von Regressionsmodellen.

Table 6: Litter FMC regression models parameters and accuracy indices.

Tabelle 6: Parameter und Genauigkeitsindizes der Regressionsmodelle für die Streu-FMC.

Model	Coefficients	Train				Test			
		$R2_{adj}$	RMSE (%)	Sy.x	AIC	$R2_{adj}$	RMSE (%)	Sy.x	AIC
Litter FMC= b0 + b1*T	b0=22.921; T=-0.246	17.99	24.03	4.39	483.97	7.68	22.98	4.26	196.41
Litter FMC= b0 + b1*RH	b0=-0.063; RH=0.293	51.35	18.51	3.38	398.84	46.84	17.16	3.18	158.88
Litter FMC= b0 + b1*W	b0=21.332; WS=-0.842	5.09	25.86	4.72	507.78	1.08	23.48	4.35	201.10
Litter FMC= b0 + b1*CC	b0=15.439; CC =4.332	5.36	25.82	4.71	507.31	1.55	23.31	4.32	200.78
Litter FMC= b0 + b1*FMC.S	b0=-1.277; FMC.S=0.697	12.83	24.78	4.52	493.91	13.53	21.84	4.05	191.96
Litter FMC= b0 + b1*VPD	b0=22.425; VPD=-0.004	37.64	20.96	3.82	439.33	19.81	21.31	3.95	186.83
Litter FMC= b0 + b1*TWI	b0=17.971; TWI=0.054	-0.58	26.62	4.86	517.24	0.07	23.71	4.39	201.80
Litter FMC= b0 + b1*T + b2*RH	b0=2.849; T=-0.073; RH=0.269	52.37	18.26	3.34	396.39	45.75	17.38	3.25	160.25
Litter FMC= b0 + b1*T + b2*RH + b3*WS	b0=4.67; T=-0.036; RH=0.296; WS=-1.109	61.61	16.34	3.00	362.19	49.15	17.08	3.21	155.85
Litter FMC= b0 + b1*T + b2*RH + b3*CC	b0=0.193; T=-0.065; RH=0.27; CC =3.939	57.06	17.28	3.17	380.48	52.50	16.21	3.05	151.23
Litter FMC= b0 + b1*T + b2*RH + b3*FMC.S	b0=-23.941; T=-0.844; RH=-0.372; FMC.S=2.93	53.14	18.05	3.32	394.71	46.03	17.28	3.25	159.91
Litter FMC= b0 + b1*T + b2*RH + b3*VPD	b0=5.364; T=0.012; RH=0.228; VPD=-0.002	53.14	18.05	3.32	394.71	46.03	17.28	3.25	159.91
Litter FMC= b0 + b1*T + b2*RH + b3*TWI	b0=2.909; T=-0.073; RH=0.269; TWI=-0.028	52.08	18.26	3.35	398.36	45.97	17.34	3.26	159.98
Litter FMC= b0 + b1*T + b2*RH + b3*WS + b4*CC + b5*FMC.S + b6*VPD + b7*TWI	b0=-39.609; T=-1.231; RH=-0.705; WS=-1.224; CC =3.925; FMC.S=4.594; VPD=0.0018; TWI=-0.08	68.70	14.61	2.72	333.80	54.57	15.99	3.11	148.19

Table 7 presents the results of predicting litter FMC using various machine learning models with all the variables and the best variables. Among the models tested, GBoost achieved the best overall performance, with an R^2_{adj} of 95.5 and a relative RMSE of 8.51% on the training data and an R^2_{adj} of 95.0 with a relative RMSE of 9.85% on the test data, indicating a good fit with minimal overfitting. RF also performed well, achieving an R^2_{adj} of 93.7 and a relative RMSE of 7.02% on the training data and an R^2_{adj} of 92.2 with a relative RMSE of 8.67% on the test data. SVM had lower accuracy, with an R^2_{adj} of 85.2 for the training data and an R^2_{adj} of 80.4 for the test data. CNN showed the weakest performance, with an R^2_{adj} of 77.3 and a relative RMSE of 12.38% on the training data and an R^2_{adj} of 71.0 and a relative RMSE of 15.33% on the test data.

When the best variables were used, GBoost continued to perform well, achieving an R^2_{adj} of 94.2 on the training data and 94.4 on the test data. RF also maintained strong performance, with an R^2_{adj} of 92.4 on the training data and 91.4 on the test data. However, the SVM model exhibited a significant decrease in performance, with an R^2_{adj} of 72.2 for the training data and 71.3 for the test data, and the CNN model exhibited a similar trend, with an R^2_{adj} of 72.5 for the training data and 76.2 for the test data (Figure 11 and Figure 12).

The models showed varying behavior when comparing these results with predictions for 1-hr FMC and 10-hr FMC. For 1-hr FMC, RF was the best overall model when all variables were used, but SVM outperformed the others when the best variables were selected. For 10-hr FMC, RF was still the top performer across all variables and the best variables. In contrast, for litter FMC, GBoost consistently outperformed all the other models, maintaining high accuracy across the training and test data. This finding suggested that GBoost is better suited for predicting litter FMC, while RF was the most reliable for 1-hr FMC and 10-hr FMC predictions (Table 7).

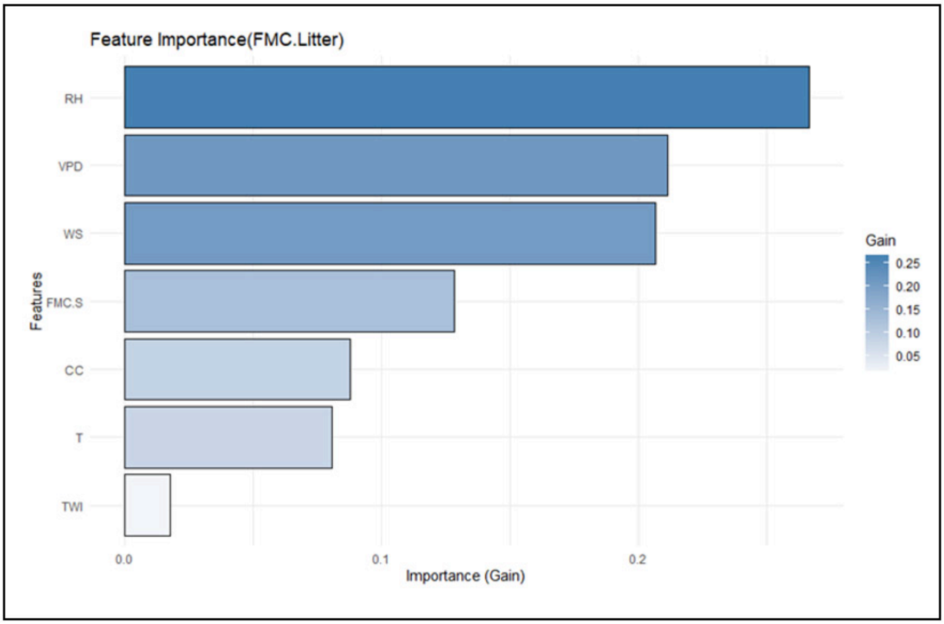

Figure 11: The relative importance of variables in predicting litter FMC using the Gain method.

Abbildung 11: Die relative Bedeutung der Variablen bei der Vorhersage der Streu-FMC mittels der Gain-Methode.

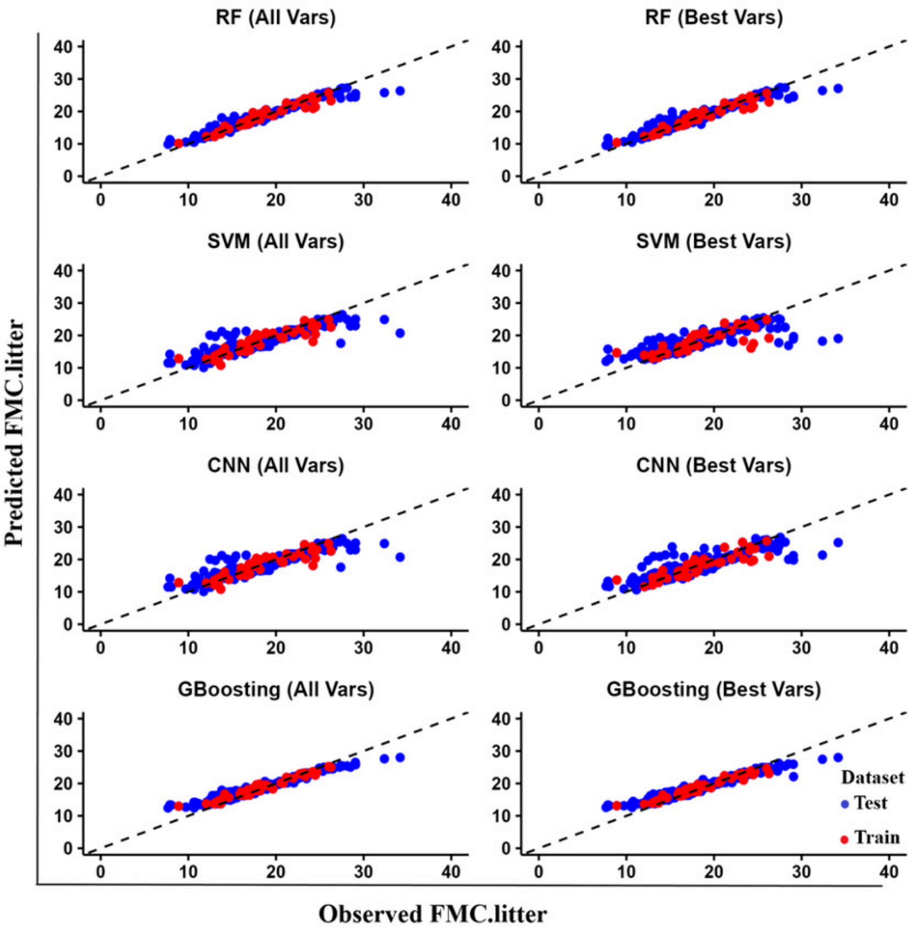

Figure 12: Scatter plot of the predicted and measured values of litter FMC using machine learning models.

Abbildung 12: Streudiagramm der vorhergesagten und gemessenen Werte der Streu-FMC unter Verwendung von maschinellen Lernmodellen.

Table 7: Litter FMC machine learning models accuracy indices.

Tabelle 7: Genauigkeitsindizes der maschinellen Lernmodelle für die Streu-FMC.

	Model	Train		Test	
		R^2adj	RMSe (%)	R^2adj	RMSe (%)
All variables	Random Forest	93.70	7.02	92.20	8.67
	SVM	85.20	17.02	80.40	17.99
	GBoost	95.50	8.51	95.00	9.85
	CNN	77.30	12.38	71.00	15.33
Best variable	Random Forest	92.40	7.55	91.40	8.92
	SVM	72.20	20.13	71.30	18.98
	GBoost	94.20	9.09	94.40	10.00
	CNN	72.50	13.54	76.20	13.82

3.3.1 Variation of Fuel Moisture Content

As an example of seasonal variation, the fuel moisture content (FMC) was predicted for 2022 using four machine learning models (RF, CNN, SVM, and GBoost), providing insights into seasonal trends across Golestan Province. Figure 13 illustrates the seasonal variation in FMC for different fuel size classes (1-hr, 10-hr, and litter), with data presented as daily averages from each model. The results indicate that FMC values were at their lowest during the summer months (days 182–244), particularly for the 1-hr and 10-hr fuel classes, highlighting heightened wildfire risk during this period due to drier fuel conditions. Conversely, FMC values began to rise in the fall and peaked during late winter and early spring (days 335–366), reflecting the seasonal dynamics driven by weather patterns in the region. The 1-hr and 10-hr fuels exhibited sharper declines and recoveries compared to the litter FMC, which retained higher moisture levels throughout the year. Across all fuel size classes, slight differences were observed between the models. The CNN and RF models showed closer alignment, particularly during the dry summer period, while SVM predictions tended to exhibit greater variability, especially for litter FMC. GBoost demonstrated smoother trends but occasionally underestimated peak FMC values during the wettest periods. These differences highlight the varying sensitivities of the models to input features and their ability to generalize seasonal FMC patterns. Despite these variations, all models captured the overall trends effectively, demonstrating their suitability for predicting FMC dynamics.

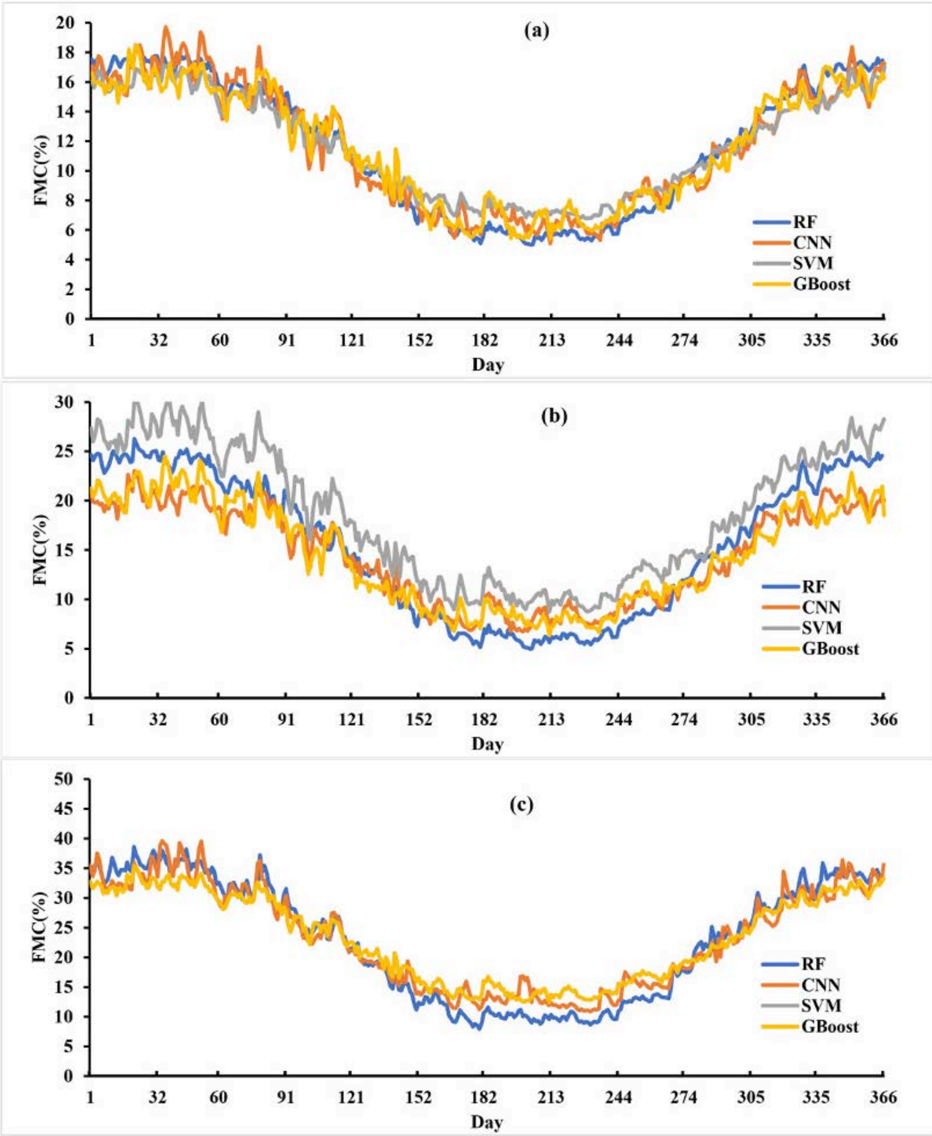

Figure 13: Average daily predicted values of FMC, using four machine learning models (RF, CNN, SVM, and GBoost), expressed as a percentage of dry weight, for 1-hr (a), 10-hr (b), and litter size classes (c) in Golestan Province for the year 2022.

Abbildung 13: Durchschnittliche tägliche vorhergesagte Werte des FMC unter Verwendung von vier maschinellen Lernmodellen (RF, CNN, SVM und GBoost), ausgedrückt als Prozentsatz des Trockengewichts, für 1-Stunde, 10-Stunde und Streu Klassen in der Provinz Golestan im Jahr 2022.

Furthermore, the spatial distribution of predicted FMC is illustrated in Figure 14 for the 1-hr, 10-hr, and litter fuel size classes, with seasonal maps presented for spring, summer, fall, and winter. These maps highlight considerable variation in FMC across Golestan Province, reflecting the influence of seasonal changes, topography, and climatic factors.

For the 1-hr fuel size class, FMC values ranged from 2% to 30%. During spring, FMC values were moderate, particularly in the mountainous areas of the south and east, where moisture levels were relatively higher. Summer exhibited the lowest FMC values, with widespread dry conditions across central and western regions. In fall, a slight recovery in moisture content was observed, especially in the eastern areas. Winter displayed the highest FMC values, with widespread moisture retention across the province.

For the 10-hr fuel size class, FMC values ranged from 5% to 35%. Spring showed moderate moisture levels, with higher values concentrated in the southern mountainous areas. Summer exhibited the most pronounced drying trends, particularly in central and western regions. In fall, moisture levels began to increase, particularly in the eastern and southern areas. Winter demonstrated the highest FMC values, with near-maximum levels across most of the province, reflecting the impact of seasonal precipitation.

The litter fuel class displayed FMC values ranging from 5% to 50%. In spring, FMC values were moderate, with higher moisture levels in the southern and eastern mountains. Summer revealed the driest conditions across all classes, with minimal moisture observed in the central and western regions. Fall indicated a gradual moisture recovery, particularly in the eastern parts of the province. Winter showcased the highest FMC values across the province, highlighting the seasonal accumulation of moisture.

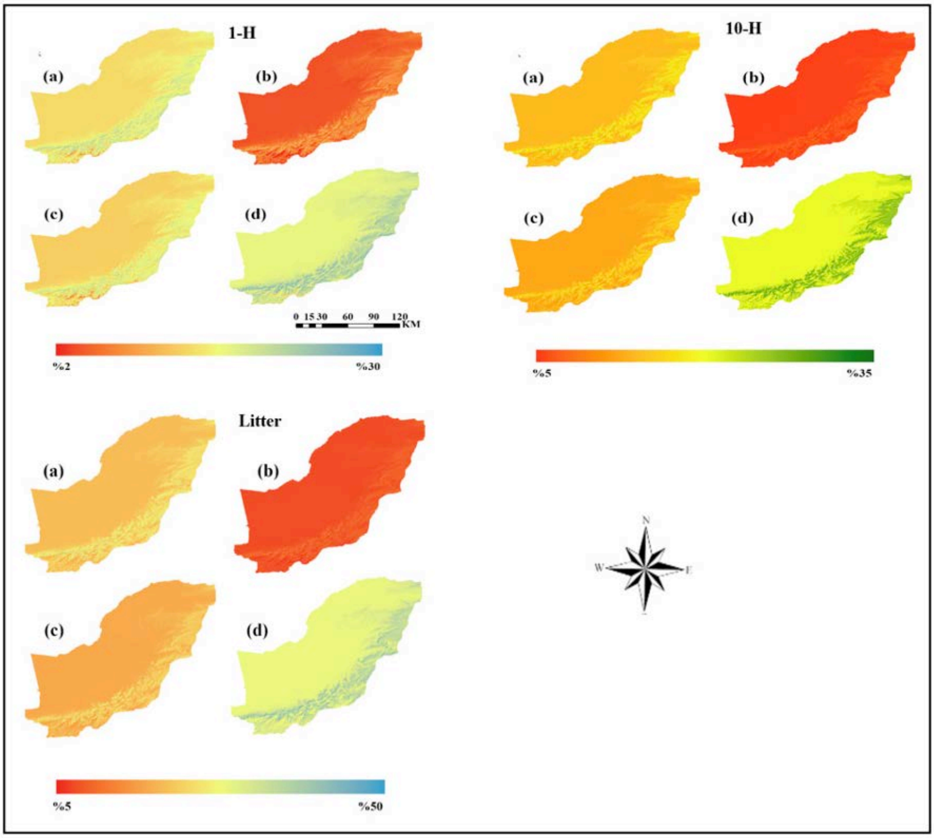

Figure 14: Spatial distribution of predicted fuel moisture content (FMC) using the best-performing model in Golestan Province for the year 2022, presented seasonally: FMC (spring (a), summer (b), fall (c), and winter (d)).

Abbildung 14: Räumliche Verteilung des vorhergesagten Brennstofffeuchtigkeitsgehalts (FMC) unter Verwendung des besten Modells in der Provinz Golestan für das Jahr 2022, saisonal dargestellt: FMC (Frühling (a), Sommer (b), Herbst (c) und Winter (d)).

4 Discussion

4.1 Performance of Different Algorithms

The present study evaluated different modeling approaches for predicting FMC across various time-lag classes and litter fuels in Golestan Province, NE Iran. The results underscore that the prediction of FMC with multivariable models performed much better than the prediction of FMC with single-variable methods for different time-lag classes (1-hr, 10-hr, and litter). Previous studies have highlighted the limitations of single-variable models in predicting FMC. Viney (1991) noted that models based only on temperature or RH often fail to capture the variability in FMC. Similarly, Nelson (2001) found that incorporating additional variables such as wind speed and solar radiation significantly improved the predictive power of FMC models. The findings from this study are consistent with these observations, underscoring the importance of a multivariable approach for accurate FMC estimation.

In comparison to those of machine learning models, the findings of these studies highlight the inadequacy of linear regression models. This deficit was further highlighted by the relatively lower R^2 recorded for the linear regression models for all time-lag classes (Nolan *et al*., 2016). In contrast, machine learning models, especially RF and SVM, demonstrated strong predictive accuracy. RF mostly achieved higher R^2 and lower relative RMSE values. This superiority is due to the ensemble learning approach of RF averaging out multiple decision trees, which enhances the predictive accuracy and makes it more stable. Moreover, nonlinear relationships modeled by the kernel functions of the SVM model have proven to be useful for handling high-dimensional data and are characteristic of FMC datasets, as supported by Rodrigues *et al*. (2024). This investigation investigated and applied the GBoost and CNN frameworks. Although these models yielded promising results, they were outperformed in this particular case by RF and SVM, though with minimal differences. The method iteratively adopted by the GBoost model to reduce prediction errors was adequate, but its computational complexity may be why it did not outperform the RF model. In contrast, the CNN model was useful for determining spatial patterns but had difficulty generalizing the relationship between the input features and FMC due to the poor spatial resolution of this dataset.

4.2 Impact of Independent Variables

The results of this study also highlight the importance of independent variables in FMC prediction. Among the univariate models, the models that used RH and VPD had greater accuracy than did the models that used other variables. According to Lee *et al*. (2020) and Masinda *et al*. (2021), RH was the most effective factor affecting FMC. A high RH slows the drying process of fuels, leading to higher FMC values, while a low RH accelerates drying. On the other hand, models containing univariate or multivariate VPD data had greater accuracy than did the other models. Generally, the VPD is increasingly recognized as an essential global metric for evaluating fire activity (Clarke *et al*., 2022; Rodrigues *et al*., 2024). Our current analysis supports that concept by suggesting that the FMC model calculated from the VPD is one of the most effective tools for predicting fuel moisture over the full range. Ignition in situations with higher VPDs is more likely to occur quickly because of the rapid drying of fuels. In addition, a high VPD may contribute to increasing spot fires (Nolan *et al*., 2016; Slijepcevic *et al*., 2015; Rodrigues *et al*., 2024).

Multivariable models have apparent advantages in precisely capturing the complex nonlinear dependencies among meteorological variables that determine variations in FMC. Single-variable models, on the other hand, while simpler and more interpretable, may omit the effects of these other factors. For example, while RH and temperature independently exert different effects on FMC, their interaction may significantly alter FMC, which is better captured in multivariable functions. This combination enables the intricacies of the conditions determining FMC to be more fully explored and, therefore, benefits the accuracy of the forecast of FMC (Fan *et al*., 2023; Lee *et al*., 2020). This research therefore confirms the findings from previous studies, such as those conducted by Yebra *et al*. (2013) and Nolan *et al*. (2016), who determined that meteorological and environmental factor-enabled models outperform simpler models in terms of FMC prediction. This may be explained by the fact that multivariate models reduce the risk of not considering relevant variables able to influence FMC and enhance the factor affecting FMC.

It is worth noting that the fuel models presented apparent differences in FMC predictions for the three classes: 1-hr, 10-hr, and litter. The 1-hr class is the smallest and most responsive fuel category; thus, this study developed the highest correlations with both RH and VPD. This is reasonable because fine fuels respond quickly to changes in atmospheric conditions; hence, they are highly sensitive to humidity and drying potential variations This sensitivity makes fine fuels particularly challenging to predict but critical for accurate fire risk assessments. The 10-hr class, which is composed of slightly larger fuels, also had a very strong correlation with RH and VPD, though this correlation was slightly weaker than that for the 1-hr fuels. This agrees with the slower response of these fuels to ambient environmental changes since they take more time to equilibrate their moisture content. In contrast, the combined fuel size and type generally had more modest correlations with RH and VPD. Greater heterogeneity within this class likely dampens the impact of individual meteorological variables to which FMC responds. Notwithstanding these differences, multivariable models systematically outperform single-variable models across all fuel classes, emphasizing the consideration of multiple factors in FMC prediction.

5 Conclusion

The results of this study justify the application of different machine learning models, with a particular emphasis on RF and SVM methods for predicting FMC across different time-lag fuel classes under different meteorological conditions in Golestan Province, NE Iran. These results outperform simple linear regression models, indicating the weakness of univariate models and echoing the strength of multivariable models. Among the various variables explored in this study, RH and VPD were determined to be the most important factors for modeling FMC, especially for fine fuels belonging to the 1-hr class. In addition, machine learning models make use of high-dimensional datasets. These results underscore the importance of advanced modeling approaches that can capture complex interactions between meteorological and topographic variables. The inclusion of machine learning models can enhance prediction systems and, by implication, the accuracy of FMC projections in forecasting and mapping FMC, serving to enhance fire risk assessment and appropriate response strategies in wildfires. The reliance on meteorological and topographical data means that other potentially important variables, such as vegetation type, soil moisture, and fuel load, were not considered. Similarly, while RH and VPD were the most important variables in this study, the importance of these variables could vary across different geographic territories or climatic environments. However, this study highlights a narrow temporal and spatial focus and limited model interpretability. Additionally, the models' performance under extreme conditions and their computational complexity may restrict real-time application.

Competing interests

The authors have declared that no competing interests exist.

Authors' contributions

All the authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Mhd. Wathek Alhaj-Khalaf, Shaban Shataee Jouibary, Roghayeh Jahdi, and William M. Jolly. The first draft of the manuscript was written by Mhd. Wathek Alhaj-Khalaf and all the authors commented on previous versions of the manuscript. All the authors read and approved the final manuscript.

Funding

The authors received no specific funding for this work.

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