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Deep learning prediction of multi-depth soil temperature using climatic variables in eastern Hungary

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Abstract

Soil temperature is a critical soil-health indicator that regulates biogeochemical processes, water balance, and carbon cycling under a changing climate. Accurate prediction of soil temperature enhances our ability to manage soil functions, sustain crop production, and mitigate climate-related risks. In this study, along with statistical exploration, we applied three predictive approaches: linear regression, random forest (RF), and a deep neural network (DNN) to predict soil temperature at depths of 5 and 50 cm in Central Europe, specifically eastern Hungary. General linear models explained a very high proportion of soil-temperature variability at both depths, with $R^2 = 0.964$ for ST5 and $R^2 = 0.913$ for ST50. Minimum air temperature was the strongest climatic predictor at both depths, followed by maximum air temperature and solar radiation, whereas wind speed had a significant negative effect and relative humidity was not significant. Season also significantly affected soil temperature during 2017–2025, while the Group $\times$ Season interaction was not significant at either depth. Although RF achieved the strongest training fit, DNN showed the most consistent validation and independent test performance. Under temporal testing at 5 cm, DNN achieved $R^2 = 0.954$, RMSE = 1.777 °C, and MAE = 1.368 °C. When applied at 50 cm, DNN retained good predictive performance, with $R^2 = 0.870$, RMSE = 2.416 °C, and MAE = 1.850 °C. These findings highlight soil temperature as a sensitive indicator of environmental change and demonstrate the value of deep learning for soil-health monitoring. The results provide a methodological and interpretive framework for integrating predictive modelling into sustainable soil and environmental management in climate-vulnerable regions.

1. Introduction

By the end of this century, the Earth's surface temperature is projected to increase by 2 °C–4 °C owing to the accelerated use of fossil fuels and mismanagement of natural resources [1]. With this rapid rise, climate change has become inevitable, driving up surface temperatures and impacting soil temperature at various depths. These shifts in soil temperature negatively affect biogeochemical processes, including evapotranspiration and the carbon cycle. As soil temperatures increase, the rate of evapotranspiration accelerates, altering the water balance and affecting nutrient availability, particularly in semi-arid and arid regions [2]. Soil temperature is a basic variable governing all biophysical and biochemical processes in terrestrial ecosystems, including seed germination, root development, microbial activities, and

surface energy exchange between land and atmosphere [3, 4]. On the terrestrial surface, soil acts as a thermal reservoir, integrating atmospheric forcing through conduction and heat storage [5]. The depth-dependent response of soil temperature is highly linked to meteorological factors. For example, most upper soil layers rapidly respond to short-term atmospheric diurnal changes, such as air temperature, incoming solar radiation (SR), and soil moisture. However, deeper soil layers respond to long-term seasonal and climatic trends [6]. Hence, understanding the soil thermal response to meteorological variability is essential for improving land-atmosphere models, sustainable agricultural productivity, and ecosystem responses to climate change [7]. Furthermore, soil temperature disrupts the carbon balance and cycle, potentially leading to increased carbon emissions into the atmosphere [8].

Traditionally, soil temperature has been monitored using several empirical and semi-empirical methods, such as simple regression with *in-situ* calibration [9]. For instance, Zhang and Li [10] performed a one-way analysis of variance (ANOVA), along with mean difference and multivariate redundancy analysis, to explain soil moisture and temperature across depths. Moreover, physical models such as agro-nomic, hydrological, and earth system models have also been reported in the literature. Empirical methods are much simpler and require less input; however, physical models are computationally intensive and require large amounts of data [11]. Recent developments in artificial intelligence (AI) and machine learning (ML) algorithms have offered a data-driven approach for monitoring multi-depth soil temperature, capturing complex and non-linear relationships, and providing more accuracy [12]. For example, Hao, Yu [13] reported that convolutional neural networks (CNN) achieved a higher prediction accuracy than support vector machines and other neural networks for temperature forecasting. For instance, Imanian, Mohammadian [14] evaluated the performance of simpler multi layer perceptron (MLP), CNN, and LSTM deep learning (DL) architectures. Coherently, Farhangmehr, Cobo [15] inferred the superior performance of CNN over MLP in predicting soil temperature under varied climatic conditions. Malik, Tikhamarine [16] employed three hybrid ML algorithms to predict daily soil temperature at different soil depths under five varying scenarios. The SVM-SMA model (Support vector machine—slime mold algorithm) had better estimates in the validation phase for scenario five at 5, 15, and 30 cm soil depths. In the arid region of Azerbaijan, MLP was the most appropriate model for predicting daily soil temperature compared to random forest (RF), M5P-based, and Gaussian process regression models [17]. For instance, Ozturk, Salman [18] in Turkey reported that ANN is reliable for predicting monthly soil temperature with temperature; correlation coefficients close to 100% for 5, 10, 20, 50 and 100 cm soil depths. In contrast, Imanian, Mohammadian [14] compared various AI methods and revealed that MLP performed better, with an R^2 of 0.980 and an NRMSE of 2.26%.

The new SVM model that treats the daily soil temperatures as a superposition of mean annual ground temperature predictions and daily ground temperature amplitude predictions was utilized by Xing, Li [19], and results revealed that the new model had mean absolute error (MAE) of 1.26 °C and RSME of 1.66 °C. compared to the conventional SVM model with the MAE of 2.20 °C and root mean squared error (RMSE) of 2.91 °C respectively. In contrast, Moazenzadeh and Mohammadi [20] exploited Elman neural network and SVR models to predict daily soil temperature at five different soil depths in Iran, identifying the outperformance of hybrid models. For instance, Singhal, Gairola [21] proposed an ANN-based model for estimating soil temperature at different soil depths of the Pindari Glacier (Central Himalaya) and revealed higher concurrence between ANN-estimated and measured air and soil temperatures. Similarly, Kisi, Sanikhani [22] utilized genetic programming, adaptive neuro-fuzzy inference system (ANFIS), and ANN-based models to forecast monthly soil temperature in Turkey. The RMSE of the ANN model was reduced by 34 and 27% at the 10 and 100 cm depths, respectively. The accuracy of the genetic programming model was higher than that of the ANN and ANFIS models at the two stations. Generally, standalone ML models, radial basis function neural networks, SVM, MLP, and particle swarm optimization can be optimized with the firefly algorithm, salp swarm algorithm, and sunflower optimization to enhance the accuracy of prediction and minimize model uncertainty [23]. Thus, the utilization of a multi-view multi-depth learning framework in situations where multiple views and depths coexist is pivotal [24]. From this perspective, prior research established sequential DL architectures for multi-depth soil temperature prediction from 10 cm to 50 cm [25].

Currently, we extend the research by evaluating classical inference methods such as ANOVA and analysis of covariance (ANCOVA) to quantify the relative contribution, effect sizes, and interaction of soil and climatic variables at shallow (5 cm) and deep (50 cm) soil layers in agricultural region of Central Europe. This will provide detailed explanatory insights with greater interpretability and agro-nomic attribution. Furthermore, complementary basic to advanced data-driven models, such as linear regression (LR), RF, and deep neural networks (DNN), were trained and tested to evaluate linear, non-linear, and complex sequential patterns at 5 cm and 50 cm. Hence, the current research extends

the scope of our dataset, providing a broader scientific contribution relevant to advanced statistical and data-driven approaches for more practical agricultural decision-making.

2. Materials and methods

2.1. Data collection and statistical analysis

Climate and soil data was obtained from the official HungaroMet Open Data Portal. This study used observations from the Debrecen Airport automatic meteorological station (station number 64 711; 47.4844° N, 21.6056° E; 106.6 m a.s.l.). The dataset included daily minimum and maximum air temperatures ($T_{\min}$ and $T_{\max}$; °C), mean wind speed (WS; m s⁻¹), mean relative humidity (RH; %), total solar radiation (RAD; J cm⁻²), and mean soil temperatures measured at depths of 5 and 50 cm. The study period extended from 1 January 2017 to 31 December 2025.

According to the information published by HungaroMet, the original observations underwent primary quality control but may not be free from inhomogeneities. Therefore, an additional quality-control assessment was conducted before the data was used in the analysis. No duplicate timestamps or physically implausible values were identified in the final dataset.

The original data had an hourly temporal resolution and was aggregated to daily values. Daily minimum and maximum air temperatures were calculated from the corresponding hourly extremes, whereas RH, WS, and soil temperatures were calculated as daily means. SR was calculated as the daily sum. Daily means and temperature extremes were retained only when at least 18 valid hourly observations were available.

Prior to applying the data-driven models, a series of classical statistical analyses were conducted to explore the underlying structure of the data and assess temporal variability. Seasonal differences in meteorological variables and soil temperature were examined using Welch's one-way ANOVA because homogeneity of variance could not be assumed. When the omnibus test was significant, Games–Howell post hoc comparisons were conducted to identify differences between individual seasons. Afterwards, ANOVA within the general linear models (GLM) frameworks was applied to quantify the effects of climatic covariates on soil temperature at 5 and 50 cm, presented as

$$ST_{d,it} = \beta_0 + \beta_1 T_{\max,it} + \beta_2 T_{\min,it} + \beta_3 RH_{it} + \beta_4 RAD_{it} + \beta_5 WS_{it} + \beta_6 Group_i + \beta_7 Season_t + \beta_8 (Group_i \times Season_t) + \varepsilon_{it}. \quad (1)$$

Where $ST_{d,it}$ presents soil temperature at depth d of 5 and 50 cm for observation i at time t , β_0 presents the intercept, $\beta_1, \beta_2, \beta_3 \dots \beta_8$ present the regression coefficients for meteorological predictors, and ε_{it} is the residual error. $Group_i$ presents two time periods (G1: 2017–2021; G2: 2022–2025). The $Season_t$ at time t presents climatological seasons classified as DJF (Dec–Feb), MAM (Mar–May), JJA (Jun–Aug), SON (Sep–Nov). All covariates were mean centred before analysis.

To verify the models' validity, we checked the assumptions and reported residual normality (Q–Q plots), homoscedasticity (Breusch–Pagan/Levene indicated heteroscedasticity), and multicollinearity using variance inflation factors. Because both models showed significant heteroscedasticity, statistical inference was based on heteroscedasticity-consistent HC3 robust standard errors. Residual independence was additionally evaluated using the Durbin–Watson statistic because the observations were recorded daily. To complement the significance tests, we reported effect sizes (partial η^2 , with ω^2 in sensitivity) to compare the relative contributions of the climatic drivers.

2.2. ML and DL framework

Google Collaboratory, commonly known as Google Colab, is a cloud-based service optimized for data science and ML. It allows collaborative coding and execution using Python while providing access to GPU and TPU resources for enhanced computational performance. Colab enables real-time collaboration by storing notebooks on Google Drive, which can be easily shared, facilitating collective code writing, data analysis, and experimentation. Functioning as an interactive lab notebook, Colab integrates both code and data manipulation capabilities, offering an environment in which code execution and output are captured directly in the notebook [26]. This concept, inspired by desktop applications such as MATLAB and Mathematical, is entirely web-based and operates through a browser. Currently, our ML and DL modelling framework was also performed in open source Google Colab for predicting soil temperature at 5 cm and 50 cm of soil depths. $T_{\min}$ (°C), $T_{\max}$ (°C), RAD (J cm⁻²), WS (m s⁻¹), and RH (%) were used as input for predictions. The two-step modelling framework was initiated by predicting soil temperature at 5 cm of soil depth using *random* and *temporal* data split methods. The dataset was

Table 1. Hyperparameters used in selected models.

Model	Hyperparameters
Linear regression	No tuned hyperparameters
Random forest	'n_estimators': [50, 100, 200], 'max_features': ['sqrt', 'log2'], 'max_depth': [10, 20, 30, None]
Deep neural network	Hidden layers = 2; neurons = 64 & 32; activation = ReLU; optimizer = Adam; loss function = MSE; epochs = 50; batch size = 32

split into 70% for training, 15% for validation, and 15% for testing for both split methods. After train test split, mean imputation was performed for filling missing data values. Imputation values were estimated exclusively from the training subset and subsequently applied to the validation and testing subsets to prevent data leakage [27]. After model's evaluation, highest performing model on test dataset at 5 cm was used as benchmark to generalize its performance at 50 cm of soil depth under the same environmental conditions.

2.2.1. Selected DL and ML algorithms

Three models were selected for predicting soil temperature at 5 cm of soil depth. These include LR, optimized RF, and a sequential DNN. A brief description of the applied models is provided below.

LR is a fundamental method used to model the linear relationship between input features and a continuous target variable. It is based on the assumption of a direct and proportional relationship between the respondent and its covariates. It has already been used in ST prediction studies [12], offering good interpretability and linear approximations [28]. The model estimates coefficients from the data to minimize prediction errors, which helps in understanding the significance of each input feature [29].

RF was applied as an ensemble non-parametric ML model, which is highly capable of capturing complex and non-linear underlying relationships. It works on the principle of bagging (constructing numerous decision trees (DTs) and averaging their outputs) to improve predictive performance and accuracy [30, 31]. In this approach, multiple DTs are constructed using bootstrap samples with replacement from the original datasets. At each node split, a random subset of predictors is selected, which introduces more variability and enhances generalization [31]. Hence, the unique combination of bootstrap sampling and random feature selection allows it to capture multi-collinearity, high-dimensional data, and complex relationships [32], making it a powerful choice over other ML models for multi-depth soil temperature prediction. Currently, RF regressor was applied to support the target-output structure. Hyperparameters were optimized using a grid search method with 10-fold cross-validation (10 CV) on the training dataset [33]. The hyperparameters used to optimize the model are presented in table 1. The final model was fitted using the best performed hyperparameter combination and predicted outcomes for train, validation, and test set were generated. A random seed of 42 was specified to ensure reproducibility, and parallel processing was used during model fitting and hyperparameter optimization.

Furthermore, the DNN was implemented in TensorFlow using the Keras Sequential API and Dense layers, while predictor variables were standardized using scikit-learn's [34, 35]. Our DNN model was comprised of two fully connected hidden layers with 64 and 32 neurons, respectively, with rectified linear unit activation functions. The output layer had one linear neuron for predicting soil temperature at 5 cm depth. The model was trained using the Adam optimizer and mean squared error (MSE) as the loss function. Training was performed for 50 epochs with a batch size of 32, while the validation dataset was used to monitor model performance during training. Hyperparameters of applied DNN are presented in table 1. Final predictions were subsequently generated for the training, validation, and test datasets.

2.2.2. Performance evaluation and uncertainty assessment

All applied ML models were evaluated using key evaluation metrics, including the coefficient of determination (R^2), RMSE, and MAE and MSE. The metrics provided a more comprehensive assessment of the model's accuracy and errors between the observed and predicted measurements, along with the ability to explain variance in linear and non-linear settings (table 2). For uncertainty assessment, 95% confidence intervals (CI) for R^2 , RMSE, MSE, and MAE were calculated using non-parametric bootstrap resampling. Observed–predicted pairs were sampled with replacement over 1000 iterations and percentile-based confidence limits were defined by the 2.5th and 97.5th percentiles of the resulting metric distribution. Additionally, we used Origin Pro and Jamovi 2.7 for advanced statistical analysis and data visualization.

Table 2. Evaluation metrics used for multi depth soil temperature prediction in machine learning.

Indicator	Equation	Range	Best fit
R^2	$1 - \frac{\sum_{i=1}^n (ST_{pred} - \overline{ST}_{obs})^2}{\sum_{i=1}^n (ST_{obs} - \overline{ST}_{obs})^2}$	0 to 1	+1
RMSE	$\sqrt{\frac{1}{n} \sum_{i=1}^n (ST_{pred} - \widehat{ST}_{obs})^2}$	0 to ∞	0
MAE	$\frac{1}{n} \sum_{i=1}^n ST_{pred} - \widehat{ST}_{obs} $	0 to ∞	0
MSE	$\frac{1}{n} \sum_{i=1}^n (ST_{pred} - ST_{obs})^2$	0 to ∞	0

3. Results

3.1. An overview of used data

The daily maximum air temperature (T_{max}) averaged $17.35\text{ }^{\circ}\text{C} \pm 10.20\text{ SD}$, with a range of $-11.00\text{ }^{\circ}\text{C}$ – $38.70\text{ }^{\circ}\text{C}$, while the minimum air temperature (T_{min}) averaged $6.78\text{ }^{\circ}\text{C} \pm 7.76\text{ SD}$ (range = $-17.00\text{ }^{\circ}\text{C}$ – $22.90\text{ }^{\circ}\text{C}$). Mean WS was $3.09\text{ m s}^{-1} \pm 1.49\text{ SD}$ (range = 0.35 – 10.82 m s^{-1}). SR averaged $1\text{ }346.85\text{ J cm}^{-2} \pm 880.44\text{ SD}$ (range = 59.60 – $3\text{ }190.20\text{ J cm}^{-2}$), and RH averaged $72.61\% \pm 15.33\text{ SD}$ (range = 30.50% – 100.00%). Mean soil temperature remained broadly similar across the four depths, while its variability and observed range progressively decreased with depth. Soil temperature at 5 cm averaged $12.98\text{ }^{\circ}\text{C} \pm 8.61\text{ SD}$ (range = $-8.32\text{ }^{\circ}\text{C}$ – $31.45\text{ }^{\circ}\text{C}$), while soil temperatures at 10 and 20 cm averaged $12.96\text{ }^{\circ}\text{C} \pm 8.36\text{ SD}$ (range = $-7.01\text{ }^{\circ}\text{C}$ – $30.53\text{ }^{\circ}\text{C}$) and $12.92\text{ }^{\circ}\text{C} \pm 7.90\text{ SD}$ (range = $-4.70\text{ }^{\circ}\text{C}$ – $28.81\text{ }^{\circ}\text{C}$), respectively. Soil temperature at 50 cm averaged $12.93\text{ }^{\circ}\text{C} \pm 6.70\text{ SD}$ (range = $-0.90\text{ }^{\circ}\text{C}$ – $24.93\text{ }^{\circ}\text{C}$) (figure 1). Although mean soil temperature differed only marginally among depths, the progressive reduction in standard deviation and temperature range with increasing depth demonstrates the stronger thermal buffering and attenuation of short-term temperature fluctuations in deeper soil layers.

Welch's ANOVA showed strong seasonal differences across the meteorological variables and soil temperatures at all four investigated depths. T_{min} showed a highly significant seasonal effect (Welch's $F(3, 1758.52) = 3460.91, p < 0.001$), followed by T_{max} (Welch's $F(3, 1780.00) = 4027.58, p < 0.001$). All pairwise comparisons were significant for T_{min} and T_{max} , except the comparison between autumn (SON; September–November) and spring (MAM; March–May), which was not significant for T_{max} . RH also varied significantly by season (Welch's $F(3, 1817.51) = 679.56, p < 0.001$), except for the spring–summer comparison (MAM versus JJA). SR (Welch's $F(3, 1744.16) = 2545.95, p < 0.001$) and WS (Welch's $F(3, 1800.14) = 45.74, p < 0.001$) also showed significant seasonal variation, with all Games–Howell pairwise comparisons being significant. Soil temperature differed significantly among the four seasons at every depth: ST5 (Welch's $F(3, 1749.85) = 9730.85, p < 0.001$), ST10 (Welch's $F(3, 1746.15) = 10\text{ }382.32, p < 0.001$), ST20 (Welch's $F(3, 1743.41) = 11\text{ }065.52, p < 0.001$), and ST50 (Welch's $F(3, 1753.28) = 10\text{ }002.58, p < 0.001$), with all Games–Howell pairwise seasonal comparisons being significant at each depth (figure 2).

3.2. Impact of climatic variables on soil temperature (ST5, ST50)

In this section, we assessed the impact of the measured climatic variables on soil temperature using a GLM. Separate ANCOVA models were fitted for soil temperature at 5 and 50 cm, with Group (G1: 2017–2021; G2: 2022–2025), Season, and the Group $\times$ Season interaction included as categorical effects and the meteorological variables included as continuous covariates. For ST5, the model was highly significant and explained most of the variance ($R^2 = 0.964, F = 7273, p < .001$). Omnibus tests showed that T_{min} , T_{max} , SR, and WS were significant predictors ($p < .001$), whereas RH was not ($p = 0.469$). T_{min} was the strongest continuous predictor, $F(1, 3264) = 1803.92, p < .001$, partial $\eta^2 p = .387$ followed by T_{max} $F(1, 3264) = 331.60, p < .001$, partial $\eta^2 p = .095$. SR also significantly influenced ST5cm, $F(1, 3264) = 270.99, p < .001$, partial $\eta^2 p = .092$, while WS had a smaller but significant effect, $F(1, 3264) = 96.71, p < .001$, partial $\eta^2 p = .033$. Furthermore, season also exhibited a significant effect on soil temperature ($F = 387.07, p < 0.001$, partial $\eta^2 p = 0.265$), whereas the difference between G1 and G2 was not significant ($F = 1.13, p = 0.287$). Further, the Group $\times$ Season interaction was non-significant, $F(3, 3264) = 1.14, p = .333$, indicating that seasonal changes in ST5cm did not differ meaningfully between the two time periods (G1 & G2) table 3.

For the second model at a soil depth of 50 cm, the model was highly significant and explained 91.3% of the variance ($R^2 = 0.913, F(12, 3264) = 2851.48, p < 0.001$). The ANOVA omnibus tests

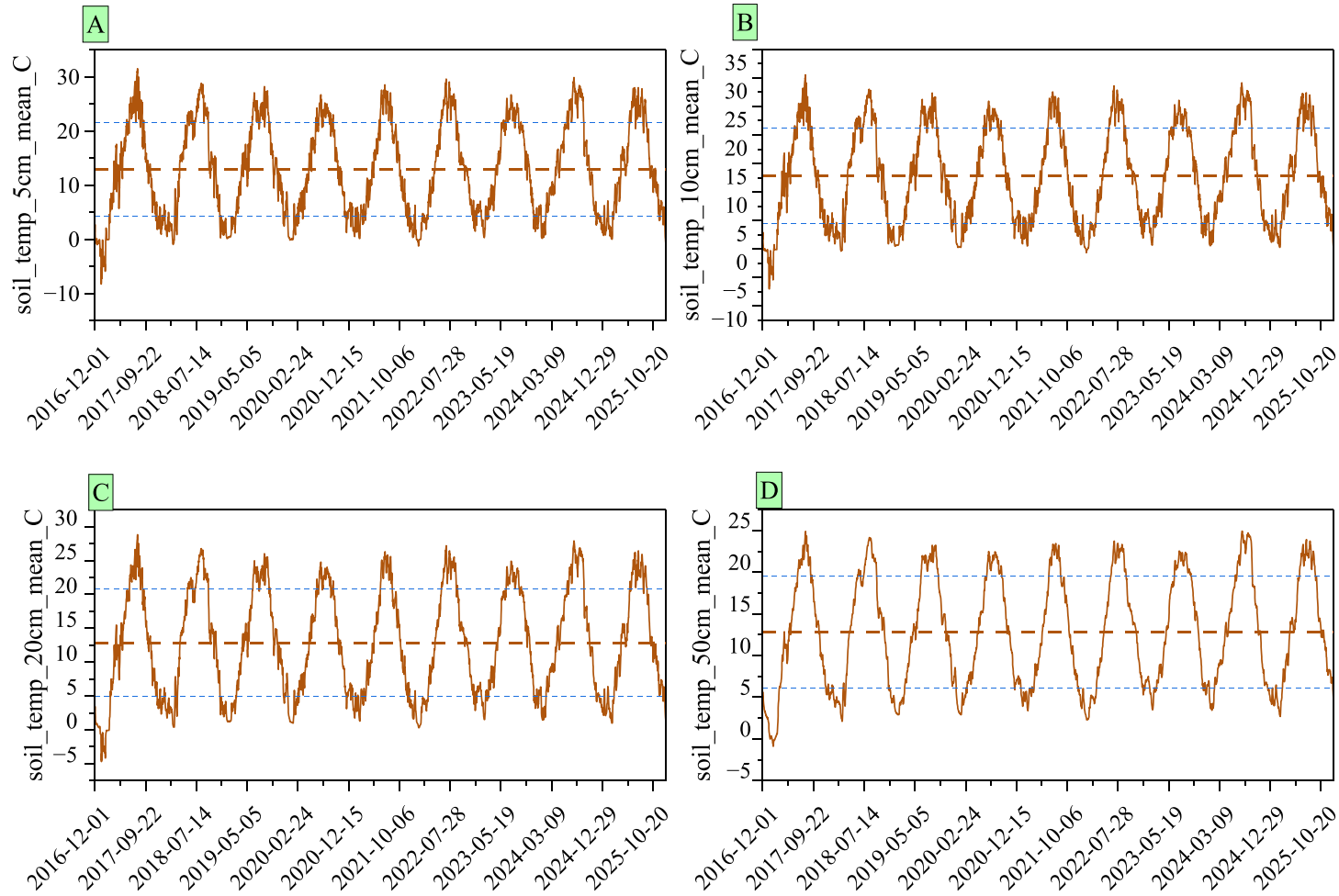


Figure 1. Daily variation in soil temperature at four depths in Debrecen, eastern Hungary, from 2017 to 2025: (a) 5-cm soil temperature (ST5), (b) 10-cm soil temperature (ST10), (c) 20-cm soil temperature (ST20), and (d) 50-cm soil temperature (ST50). Panels (e)–(h) show the corresponding 356 day moving-average series for ST5, ST10, ST20, and ST50, respectively. The analysis included 3286 daily observations at each soil depth.

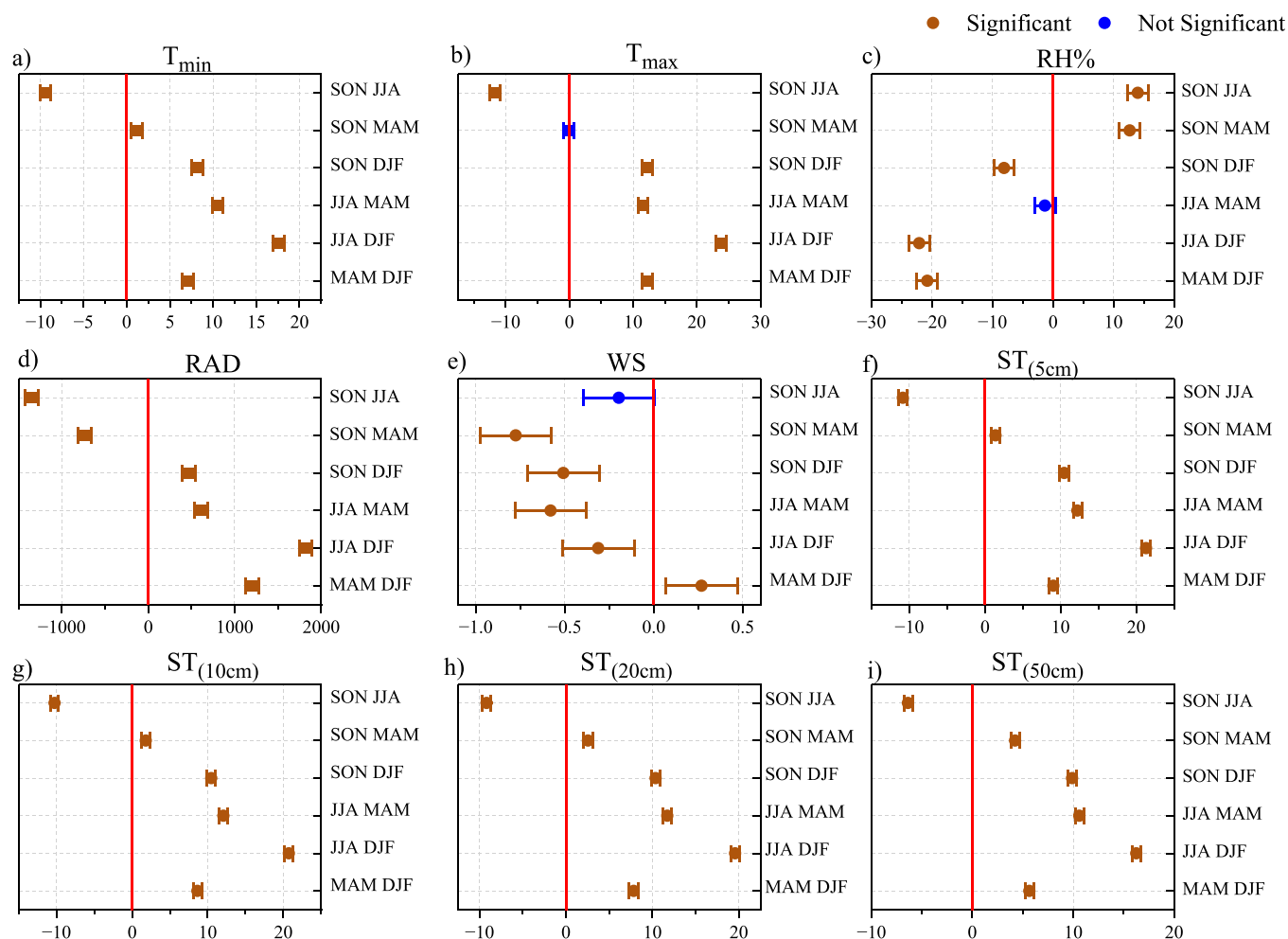


Figure 2. Games–Howell post-hoc comparisons following Welch's ANOVA for seasonal differences in (a) minimum air temperature ($T_{\min}$), (b) maximum air temperature ($T_{\max}$), (c) mean relative humidity (RH), (d) daily solar-radiation sum (RAD), (e) mean wind speed (WS), and soil temperature at (f) 5 cm ($ST_{5\text{cm}}$), (g) 10 cm ($ST_{10\text{cm}}$), (h) 20 cm ($ST_{20\text{cm}}$), and (i) 50 cm ($ST_{50\text{cm}}$) during 2017–2025. Points represent pairwise mean differences calculated as the first season minus the second season, and horizontal error bars represent 95% confidence intervals. The red vertical line indicates no difference between seasons. Seasons are defined as DJF (December–February), MAM (March–May), JJA (June–August), and SON (September–November).

Table 3. ANOVA/GLM Omnibus tests for ST 5 cm and 50 cm.

	SS	df	F	<i>p</i>	η^2	$\eta^2 p$	ω^2	$\omega^2 p$	ϵ^2	$\epsilon^2 p$
ST5cm										
Model	234 345.097	12	7272.741	<.001	0.96395	0.964	0.964	0.964	0.964	0.964
Group	2.989	1	1.133	0.287	1.23e-5	0.000	0.000	0.000	0.000	0.000
Season	3162.246	3	387.072	<.001	0.01301	0.265	0.013	0.264	0.013	0.264
Air_temp_min_C	5533.939	1	1803.921	<.001	0.02276	0.387	0.023	0.386	0.023	0.387
Air_temp_max_C	923.935	1	331.604	<.001	0.00380	0.095	0.004	0.095	0.004	0.095
Relative_humidity_mean_pct	1.760	1	0.525	0.469	7.24e-6	0.000	0.000	0.000	0.000	0.000
Solar_radiation_sum_J_cm2	889.814	1	270.988	<.001	0.00366	0.092	0.004	0.092	0.004	0.092
Wind_speed_mean_m_s	297.028	1	96.705	<.001	0.00122	0.033	0.001	0.032	0.001	0.032
Group * Season	10.102	3	1.136	0.333	4.16e-5	0.001	0.000	0.000	0.000	0.000
Residuals	8764.490	3264								
Total	243 109.588	3276								
ST50cm										
Model	134 021.212	12	2851.482	<.001	0.91292	0.913	0.913	0.913	0.913	0.913
Group	37.096	1	9.725	0.002	2.53e-4	0.003	0.000	0.003	0.000	0.003
Season	10 752.758	3	861.236	<.001	0.07324	0.457	0.073	0.456	0.073	0.456
Air_temp_min_C	2749.284	1	666.179	<.001	0.01873	0.177	0.019	0.176	0.019	0.177
Air_temp_max_C	143.336	1	36.424	<.001	9.76e-4	0.011	0.001	0.011	0.001	0.011
Relative_humidity_mean_pct	4.986	1	1.109	0.292	3.40e-5	0.000	0.000	0.000	0.000	0.000
Solar_radiation_sum_J_cm2	416.242	1	92.712	<.001	0.00284	0.032	0.003	0.031	0.003	0.031
Wind_speed_mean_m_s	149.596	1	35.037	<.001	0.00102	0.012	0.001	0.011	0.001	0.011
Group * Season	3.156	3	0.277	0.842	2.15e-5	0.000	0.000	0.000	0.000	0.000
Residuals	12 784.150	3264								
Total	146 805.362	3276								

showed that $T_{\min}$ was the strongest continuous predictor, $F(1, 3264) = 666.18$, $p < 0.001$, $\eta^2 = 0.177$, followed by $T_{\max}$, $F(1, 3264) = 36.42$, $p < 0.001$, $\eta^2 = 0.011$. SR and WS were also significant predictors of ST50, whereas relative humidity was not significant ($p = 0.292$). Season had a strong effect, $F(3, 3264) = 861.24$, $p < 0.001$, $\eta^2 = 0.457$, while Group had a statistically significant but very small effect, $F(1, 3264) = 9.73$, $p = 0.002$, $\eta^2 = 0.003$. The Group $\times$ Season interaction was non-significant, $F(3, 3264) = 0.28$, $p = 0.842$ (table 3).

The standardized coefficient estimates from ANOVA analysis indicated that both maximum air temperature ($T_{\max}$) and minimum air temperature ($T_{\min}$) were positively associated with soil temperature at both depths. $T_{\max}$ showed significant positive associations with ST5cm ($\beta = .243$, $p < .001$) and ST50cm ($\beta = .123$, $p < .001$), while $T_{\min}$ showed stronger positive associations with ST5cm ($\beta = .484$, $p < .001$) and ST50cm ($\beta = .439$, $p < .001$). SR also showed a positive association with ST5cm ($\beta = .157$, $p < .001$) and ST50cm ($\beta = .138$, $p < .001$). However, WS showed a negative association with ST5cm ($\beta = -0.041$, $p < .001$) and ST50cm ($\beta = -0.038$, $p < .001$) (figures 3(a) and (d)). The seasonal effect was stronger at 50 cm ($\eta^2 p = 0.457$) than at 5 cm ($\eta^2 p = 0.265$), as indicated by the larger partial effect size. At both depths, the absence of a significant Group $\times$ Season interaction indicates that the seasonal soil-temperature cycle remained statistically stable between the two study periods (figures 3(c) and (f)). The statistically significant Group effect observed at 50 cm therefore represents a modest shift in deeper-soil temperature rather than a major alteration of its seasonal dynamics. Model diagnostics indicated significant heteroscedasticity according to both the Breusch–Pagan and Levene tests at 5 and 50 cm; therefore, inference was based on heteroscedasticity-consistent robust standard errors. Residual normality was visually acceptable based on the Q–Q plots and residual histograms, particularly for the 50 cm model, although formal normality tests were interpreted cautiously because of the large sample size.

3.3. Performance evaluation of ML and DL under 5 cm of soil depth

After statistical evaluation, soil-temperature predictions at 5 cm showed consistently high model performance. Initial prediction of soil temperature at 5 cm using random data splitting showed the best training fit for RF, with $R^2 = 0.986$ (95% CI: 0.985–0.987), RMSE = 1.034 °C (1.002–1.066), MAE = 0.814 °C (0.787–0.839), and MSE = 1.070 °C² (1.004–1.135). This was followed by DNN, with $R^2 = 0.960$ (0.957–0.963), RMSE = 1.733 °C (1.678–1.789), MAE = 1.351 °C (1.306–1.396), and MSE = 3.003 °C² (2.816–3.199) (figure 4). LR had the lowest training accuracy, with $R^2 = 0.952$ (0.949–0.955), RMSE = 1.889 °C (1.834–1.944), MAE = 1.493 °C (1.447–1.539), and MSE = 3.569 °C² (3.362–3.779) (appendix table A1).

Independent validation showed competitive performance between DNN and RF. DNN slightly outperformed RF numerically, with $R^2 = 0.957$ (0.949–0.963), RMSE = 1.765 °C (1.637–1.893), MAE = 1.355 °C (1.249–1.460), and MSE = 3.116 °C² (2.681–3.582). RF ranked second on the validation set, with $R^2 = 0.956$ (0.949–0.962), RMSE = 1.787 °C (1.658–1.904), MAE = 1.391 °C (1.287–1.486), and MSE = 3.192 °C² (2.749–3.626). However, the overlapping CI indicate that the difference between DNN and RF was small. Evaluation on the independent test set again identified DNN as the numerically best-performing model, with $R^2 = 0.953$ (0.945–0.960), RMSE = 1.870 °C (1.749–1.996), MAE = 1.465 °C (1.366–1.570), and MSE = 3.496 °C² (3.058–3.986) (figure 5). This was followed closely by RF, with $R^2 = 0.952$ (0.944–0.960), RMSE = 1.879 °C (1.741–2.004), MAE = 1.471 °C (1.364–1.574), and MSE = 3.529 °C² (3.032–4.015) (appendix table A1). Thus, DNN provided the best overall validation and test performance under random splitting, although its advantage over RF was modest.

Under temporal data splitting, RF again achieved the best training fit, with $R^2 = 0.985$ (0.984–0.986), RMSE = 1.049 °C (1.018–1.081), MAE = 0.822 °C (0.795–0.848), and MSE = 1.101 °C² (1.037–1.169). DNN ranked second during training, achieving $R^2 = 0.960$ (0.957–0.963), RMSE = 1.742 °C (1.688–1.794), MAE = 1.362 °C (1.320–1.405), and MSE = 3.034 °C² (2.850–3.219) (figure 4). However, during independent temporal validation, LR achieved the highest R^2 and lowest RMSE, with $R^2 = 0.947$ (0.937–0.955), RMSE = 1.848 °C (1.724–1.982), MAE = 1.445 °C (1.346–1.551), and MSE = 3.415 °C² (2.972–3.929) (appendix table A1). The validation performances of the three models were nevertheless very similar, as indicated by their overlapping CI.

RF showed evidence of overfitting because its excellent training performance was not maintained during validation and testing under either splitting strategy (figure 5). Final evaluation using the temporally independent test set showed that DNN achieved the best performance, with $R^2 = 0.954$ (0.945–0.961), RMSE = 1.777 °C (1.652–1.905), MAE = 1.368 °C (1.278–1.471), and MSE = 3.159 °C²

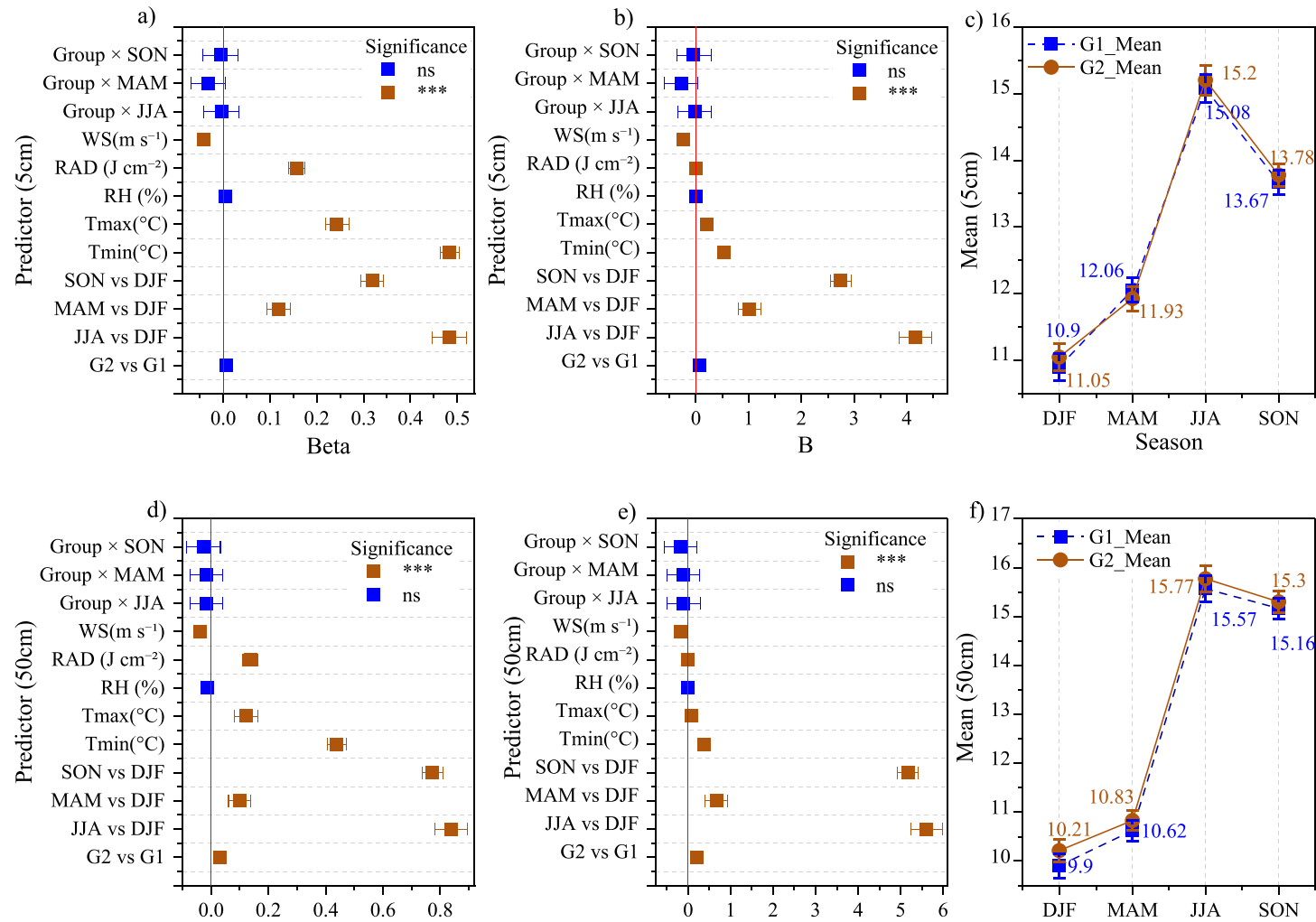


Figure 3. General linear model results for soil temperature at 5 and 50 cm. Panels (a) and (d) show the standardized coefficient estimates (β) with 95% confidence intervals for ST5 and ST50, respectively; panels (b) and (e) show the corresponding unstandardized coefficient estimates (B) with 95% confidence intervals; and panels (c) and (f) present the estimated marginal means of soil temperature for the Group $\times$ Season combinations at 5 and 50 cm, respectively. Brown symbols indicate statistically significant effects ($p < 0.001$), whereas blue symbols indicate non-significant effects. Error bars in panels (c) and (f) represent 95% confidence intervals. G1 represents 2017–2021, G2 represents 2022–2025, and DJF, MAM, JJA, and SON denote winter, spring, summer, and autumn, respectively.

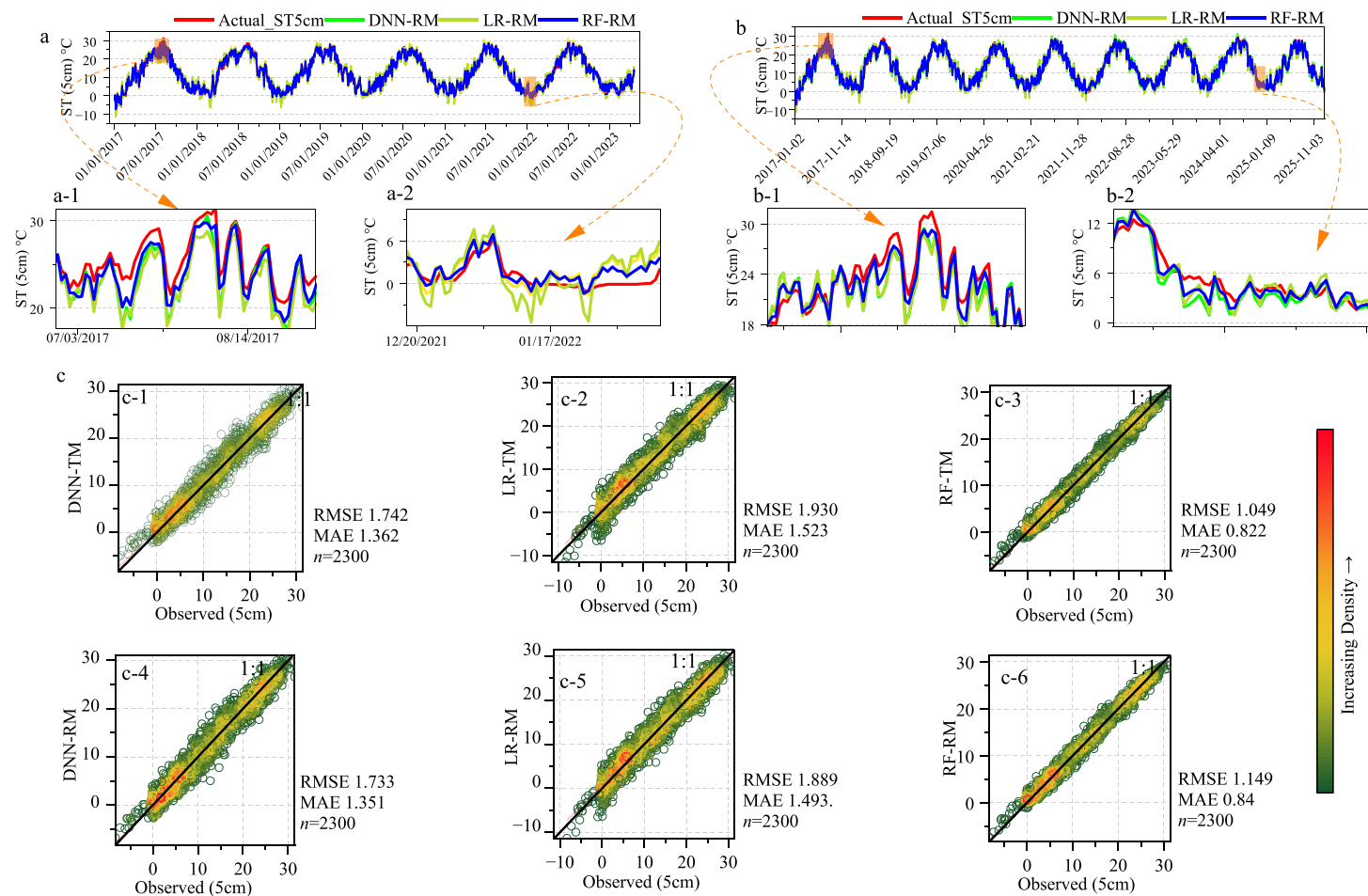


Figure 4. Training-stage performance of linear regression (LR), deep neural network (DNN), and random forest (RF) models for soil-temperature prediction at 5 cm under temporal (TM) and random (RM) data-splitting strategies. Panels (a) and (b) show the observed and model-predicted soil-temperature time series under temporal and random splitting, respectively, with panels (a-1, a-2) and (b-1, b-2) providing enlarged views of selected periods. Panels (c-1–c-3) show density-coloured observed-versus-predicted relationships for DNN, LR, and RF under temporal splitting, whereas panels (c-4–c-6) show the corresponding relationships under random splitting. The solid black line represents the 1:1 agreement line. RMSE and MAE are reported in °C; $n = 2\,300$.

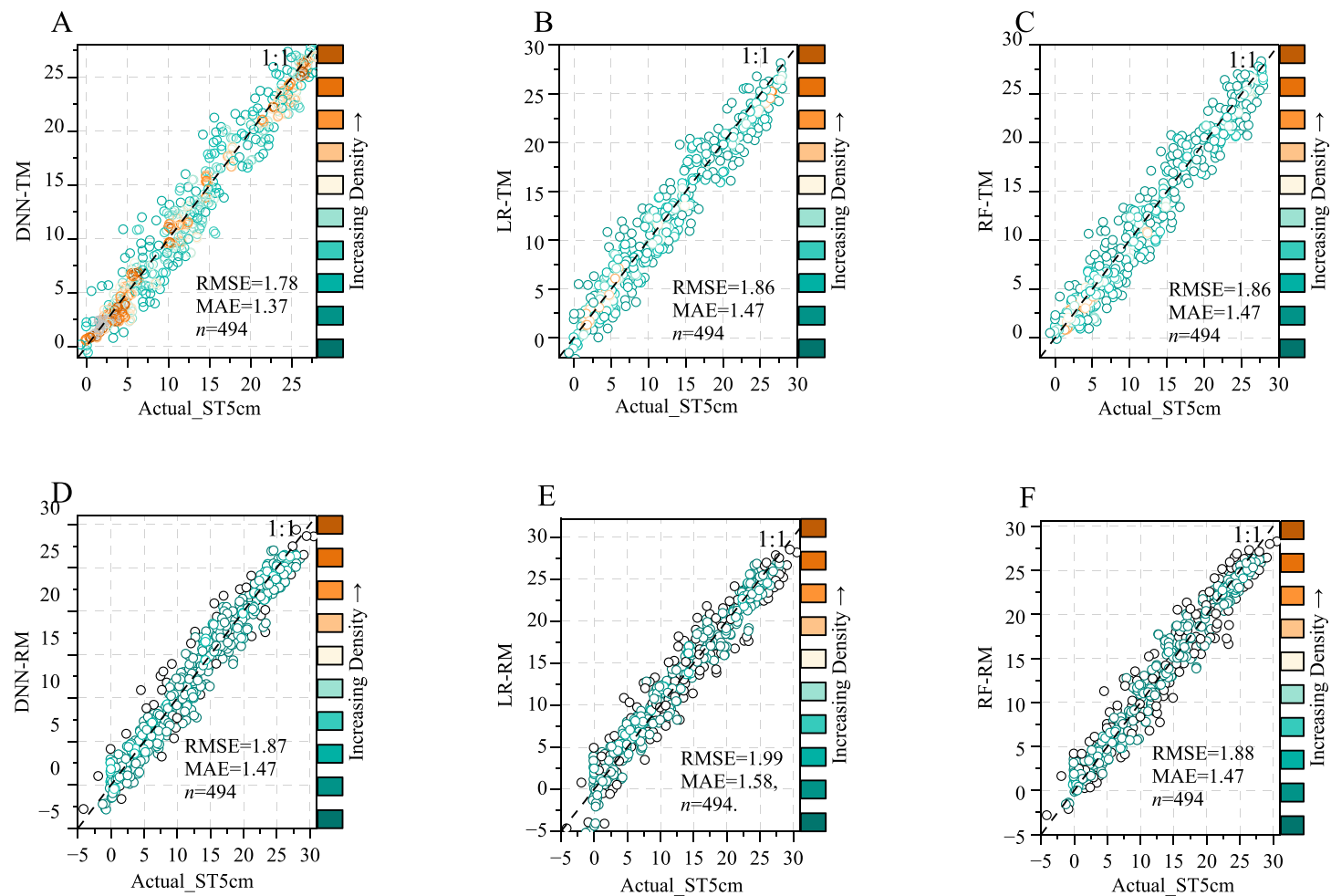


Figure 5. Density-coloured observed-versus-predicted relationship of Test-stage characteristics of the DNN, LR, and RF models for predicting soil temperature at 5 cm under temporal (TM) and random (RM) data splitting. Panels (A), (B), and (C) show density-coloured observed-versus-predicted relationship for DNN-TM, LR-TM, and RF-TM, respectively, while panels (D), (E), and (F) show the corresponding results for DNN-RM, LR-RM, and RF-RM.

(2.730–3.627). DNN therefore demonstrated the most consistent generalization performance across the validation and test sets under both random and temporal splitting, with RMSE values ranging from 1.765 to 1.871 °C (figure 5).

Accordingly, DNN was selected as the best-performing model at 5 cm and was subsequently applied to soil-temperature prediction at 50 cm. At 50 cm, DNN achieved $R^2 = 0.870$ (95% CI: 0.861–0.877), RMSE = 2.416 °C (95% CI: 2.347–2.489), and MAE = 1.850 °C (95% CI: 1.797–1.905), demonstrating good predictive capability at the deeper soil layer (figure 6). The observed–predicted correlation was $r = 0.933$ ($p < 0.001$), while the mean residual bias was only 0.05 °C. Nevertheless, the residuals retained substantial temporal dependence, with a lag-1 autocorrelation of 0.769, indicating that some short-term temporal structure remained unexplained by the model.

Finally, although RF produced the strongest training fit, DNN demonstrated better and more stable performance on independent test data, particularly under temporal splitting, and therefore provided the most reliable generalization among the three evaluated models.

4. Discussion

Multi-depth soil temperature dynamics offers deep insight into the soil thermal regime regulated by atmospheric forcing and land surface changes [3, 36]. Our research findings validate the thermal diffusion behaviour characterized by the transmission of surface energy down the soil column [37]. Upper soil layers (0–5 cm) are more responsive to daily fluctuations in air temperature and SR than deeper layers, depending on other seasonal and meteorological factors. Based on partial η^2 , three strongest contributors were $T_{\min}$ ($\eta^2 p = 0.3877$), $T_{\max}$ ($\eta^2 p = 0.095$), and SR = 0.092. For instance, daytime heating from net shortwave radiation increases the near-surface soil temperature more rapidly, whereas long-wave cooling promotes surface energy loss [38, 39]. Therefore, the upper soil layers (5–10 cm) exhibit a strong diurnal cycle closely related to the maximum and minimum air temperatures [40], and 50-cm layer showed stronger seasonality and attenuated short-term atmospheric responses. The relationship weakens in depth because of the conduction lagging the signal response. For instance, previous research by Malik, Tikhmarine [16], Jing and Wang [39], and Farhangmehr, Cobo [15] also proved that air temperature and SR are significant causes of multi-depth soil temperature. Furthermore, precipitation, WS, and humidity are crucial factors affecting soil temperature [41]. High relative humidity reduces the evaporative demand, enhancing the effect of warmed radiation on the soil surface [16]. Similarly, dry winds enhance turbulent exchange and evaporative losses, which divert energy away from the sensible heating of the soil and result in lower soil temperature increases. Currently, the WS effect was found to be small ($\eta^2 p = 0.033$) at 5 cm in combination with other meteorological factors. Moreover, soil moisture also influences the thermal characteristics of the soil, as it redistributes surface energy between latent and sensible heat fluxes [42, 43]. Wet soils, with higher heat capacities, warm and cool more slowly but conduct the thermal wave more effectively to depth, whereas dry soils intensify surface heating and amplify shallow thermal gradients [43]. Spatial heterogeneity in biophysical factors, such as vegetation cover and topographical characteristics, also influences the distribution pattern of soil temperature [44, 45]. Currently, the temporal pattern of soil temperature has only been analysed from the agricultural landscape of Central Europe with distinct phenological patterns of crop growth. During peak vegetation growth, incoming SR is interrupted from reaching deeper soil, causing a lag or seasonal effect. Hence, vegetation cover strongly acts as an insulator, declining the amplitude of soil thermal properties [46]. Among the topographic factors, slope and aspect also modify the incident radiation, producing local soil thermal regimes under similar meteorological forcing [44].

Our research findings highlighted the significance of meteorological factors affecting soil temperature from 5 cm to 50 cm across the agricultural landscape of central Europe. The upper soil layer of 5 cm proved to be more responsive to short-term atmospheric variations, while deep soil thermal properties were strongly influenced by relative humidity and soil moisture, along with long-term seasonal effects. These insights are crucial for agricultural decision-makers to evaluate land-atmospheric feedback under climate change phenomena.

Following the statistical exploration, ML-based comparison of three predictive models revealed that the RF outperformed while model's training in both data split methods. The numerically outperformance of RF compared to other models in training is attributed to its powerful algorithmic structure, particularly its ability to handle complex environmental and agricultural problems [32, 35]. A recent study by Tan, Luo [47] also validated the outperformance of RF for the recreation of soil temperature datasets. RF operates by constructing multiple DTs based on different subsets of data (using bootstrap

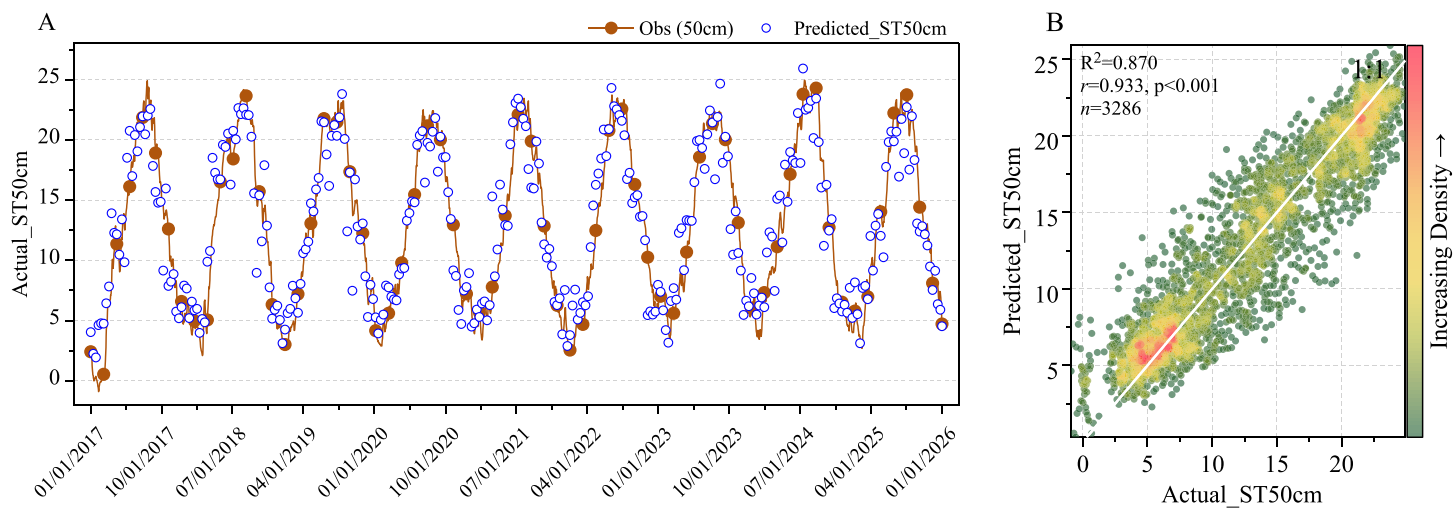


Figure 6. Cross-depth DNN performance for predicting soil temperature at 50 cm. (a) Temporal comparison of observed and predicted soil temperatures; (b) density-coloured observed-versus-predicted relationship, with the white line indicating 1:1 agreement.

sampling) and the features. Overall, the ensemble approach of RF reduce the risk of overfitting, making the model more generalizable and capable of performing well on unseen data [35]. However, currently the model showed a marked training-validation gap indicating less generalization on test sets. On contrary, RF outperformance in soil temperature prediction had been reported in other previous soil property studies [48, 49], attributed to its ability to handle high-dimensional datasets, where many input variables interact, which is particularly beneficial for tasks such as soil temperature prediction, where environmental and soil characteristics are complex and interdependent [32]. However, LR showed marginally lower RMSE and MSE and a slightly higher R^2 on the temporal validation subset, suggesting a linear relationship between covariates and multi depth soil temperature. Exceptionally strong performance of RF during training showed clear evidence of overfitting. Its RMSE increased from 1.049 during training to 1.872 during validation, while R^2 declined from 0.985 to 0.946. This substantial training-validation gap indicates that the model captured patterns specific to the training period but could not generalize equally well to validation and testing sets.

Another previous research by Feng, Cui [50] found extreme learning machine, a kind of Deep Neural Network to outperform over RF. DL models are able to predict varied soil properties across different regions of world [51–55]. Similar previous research by Mohammed, Arshad [25] also reported the superior performance of sequential DL models for predicting multi depth soil temperature in eastern Mediterranean region. Currently, our research findings also demonstrated a superior performance by DNN on test sets in both random and temporal data split methods. DNN showed a smaller generalization gap and subsequently achieved the best performance on the independent temporal test subset, with an RMSE of 1.777 and an R^2 of 0.954. Overall, these findings support DNN as the most reliable model for temporal generalization.

5. Limitations

Our research provides significant findings of predicting soil temperature from environmentally covariate in agricultural settings of central Europe. A few limitations are also acknowledged while interpreting the findings. First, our study utilized datasets from a single monitoring station limiting generalization at broader spatial scale with different soil, vegetation, and climatic characteristics. The models did not include several potentially important soil and land-surface characteristics which could be considered in future research. The 5 and 50 cm observations were obtained from the same station and observation period; therefore, the evaluation at 50 cm should be interpreted as a cross-depth transferability assessment rather than fully independent external validation. Second, our study used random and temporal data split methods with high prediction accuracy on unseen test set. However, temporal autocorrelation must be considered while interpreting these findings. RF also exhibited a marked training-to-validation performance gap, indicating potential overfitting. Future research could incorporate more ML and DL experiments incorporating multiple algorithms and extensive hyperparameter optimization. Future studies should validate models using temporally independent datasets from multiple stations and incorporate additional soil, vegetation, and hydrological predictors.

6. Conclusion

Tracking changes in soil temperature is vital for understanding soil processes and their responses to environmental and climatic changes. This research focused on Central Europe, particularly eastern Hungary, a region increasingly affected by prolonged drought events and heatwaves. The results revealed that soil temperature is strongly governed by atmospheric conditions. At 5 cm depth, minimum air temperature was the dominant climatic predictor of soil temperature (partial $\eta^2 = 0.387$), followed by maximum air temperature (partial $\eta^2 = 0.095$), SR (partial $\eta^2 = 0.092$), and WS (partial $\eta^2 = 0.033$), whereas relative humidity had no significant effect. Although RF achieved the strongest training fit, the DNN demonstrated the most consistent validation and independent test performance. Under temporal testing at 5 cm, DNN achieved $R^2 = 0.954$, RMSE = 1.777 °C, and MAE = 1.368 °C, supporting its selection as the best-generalizing model.

Overall, the DNN was the most robust and reliable model, capturing the nonlinear relationships and interactions governing soil-temperature variability. Future work should refine the DNN architecture through systematic hyperparameter optimization and consider ensemble strategies and feature engineering, including mean air temperature and diurnal temperature range, to further reduce prediction errors and improve the interpretation of variable importance.

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Data availability statement

The data used in this study are freely available through the HungaroMet Open Data Portal.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this study.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used Claude and Paperpal for language editing and clarity improvement. All AI-assisted outputs were critically reviewed and edited by the authors, who take full responsibility for the content, accuracy, and integrity of the final manuscript.

Appendix

Table A1. Evaluation metrics of ML and DL models at 5 cm of soil depth

Scenario	Data split	Dataset	Model	MSE (°C) (95% CI)	RMSE (°C) (95% CI)	R ² (95% CI)	MAE (°C) (95% CI)
SC—1	Random	Train	Linear regression	3.569 (3.362–3.779)	1.889 (1.834–1.944)	0.952 (0.949–0.955)	1.493 (1.447–1.539)
		Train	Random forest	1.070 (1.004–1.135)	1.034 (1.002–1.066)	0.986 (0.985–0.987)	0.814 (0.787–0.839)
		Train	DNN	3.003 (2.816–3.199)	1.733 (1.678–1.789)	0.960 (0.957–0.963)	1.351 (1.306–1.396)
		Validation	Linear regression	3.619 (3.123–4.177)	1.902 (1.767–2.044)	0.950 (0.940–0.957)	1.472 (1.366–1.585)
		Validation	Random forest	3.192 (2.749–3.626)	1.787 (1.658–1.904)	0.956 (0.949–0.962)	1.391 (1.287–1.486)
		Validation	DNN	3.116 (2.681–3.582)	1.765 (1.637–1.893)	0.957 (0.949–0.963)	1.355 (1.249–1.460)
		Test	Linear regression	3.952 (3.438–4.433)	1.988 (1.854–2.105)	0.947 (0.938–0.954)	1.581 (1.479–1.681)
		Test	Random forest	3.529 (3.032–4.015)	1.879 (1.741–2.004)	0.952 (0.944–0.960)	1.471 (1.364–1.574)
		Test	DNN	3.496 (3.058–3.986)	1.870 (1.749–1.996)	0.953 (0.945–0.960)	1.465 (1.366–1.570)
SC—2	Temporal	Train	Linear regression	3.726 (3.516–3.980)	1.930 (1.875–1.995)	0.950 (0.947–0.954)	1.523 (1.479–1.573)
		Train	Random forest	1.101 (1.037–1.169)	1.049 (1.018–1.081)	0.985 (0.984–0.986)	0.822 (0.795–0.848)
		Train	DNN	3.034 (2.850–3.219)	1.742 (1.688–1.794)	0.960 (0.957–0.963)	1.362 (1.320–1.405)
		Validation	Linear regression	3.415 (2.972–3.929)	1.848 (1.724–1.982)	0.947 (0.937–0.955)	1.445 (1.346–1.551)
		Validation	Random forest	3.505 (3.022–4.052)	1.872 (1.738–2.013)	0.946 (0.936–0.955)	1.435 (1.338–1.530)
		Validation	DNN	3.500 (3.033–3.993)	1.871 (1.742–1.998)	0.946 (0.935–0.954)	1.452 (1.353–1.546)
		Test	Linear regression	3.446 (3.034–3.893)	1.856 (1.742–1.973)	0.950 (0.941–0.957)	1.468 (1.370–1.564)
		Test	Random forest	3.445 (3.051–3.906)	1.856 (1.747–1.976)	0.950 (0.941–0.957)	1.465 (1.375–1.571)
		Test	DNN	3.159 (2.730–3.627)	1.777 (1.652–1.905)	0.954 (0.945–0.961)	1.368 (1.278–1.471)

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