Impact factors and dynamic simulation of tillage-layer temperature in frozen-thawed soil under different cover conditions

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Abstract: Based on a winter field experiment between 2016 and 2017, four treatments (bare land (BL), natural snowfall coverage (NS), 5-cm-deep straw + natural snowfall coverage (SC5), and 10-cm-deep straw + natural snowfall coverage (SC10)) were established to determine the effects of the different treatments on soil temperature at the soil surface and at depths of 10 cm, 20 cm, and 30 cm. The environmental factors of ambient temperature, ambient humidity, water vapor pressure, 10-min wind speed, total radiation, net radiation, and long wave radiation were obtained from the weather station in the study area. Through correlation, multiple regression, and stepwise regression analysis, models for dynamic simulation of the tillage-layer soil temperature were constructed for analyzing the relation between tillage-layer soil temperature and environmental factors. The results showed that the environmental factors were all significantly correlated with tillage-layer temperature at the 0.01 level; when the impacts of other environmental factors were excluded, the correlations decreased significantly. The dynamic simulation models for tillage-layer soil temperature under different coverage conditions were different, and the larger the coverage amount, the fewer the environmental factors that could affect the tillage-layer temperature. The coefficients of determination of the prediction results of the dynamic models for the tillage-layer soil temperature under the four treatments (BL, NS, SC5, and SC10) were 0.8385, 0.7110, 0.7283, and 0.6216, respectively. The prediction had a high accuracy and can accurately depict the dynamic changes of the tillage-layer soil temperature. The results provided a theoretical basis for the efficient utilization of farmland soil water and heat resources.

Keywords: farmland cover condition, frozen-thawed soil, tillage-layer temperature, impact factor, dynamic simulation, stepwise regression

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1 Introduction

As an important part of the underlying surface of land, soil has very important influences on the heat exchange between the land and the atmosphere[1,2], especially on the tillage soil layer. Under the constraints of environmental factors, soil heat exchange in the tillage soil layer shows different patterns of periodic variations[3,4]. The changes in the internal temperature of the tillage soil layer have important impacts on soil respiration[5], salt and water transport, and crop yield[6,7].

In China, frozen soil accounts for approximately 53.5% of the country's land acreage and is widespread in arid and semi-arid areas with water shortages in Northeast, Northwest, and North China[8]. Due to the environmental impact, spring droughts, which have seriously affected the development of agricultural production and the improvement of regional food security, often occur in these areas[9]. Therefore, accurate analysis of the factors that impact the tillage-layer soil temperature and a further dynamic simulation of its changes can be of great theoretical and practical significance for the efficient use of water and heat resources in frozen-thawed soil and for reducing the impact of spring drought on agricultural production[10,11]. As the tillage-layer soil is in close contact with the external environment, its temperature changes have a close association with environmental factors[12,13], and many researchers have conducted studies on this topic. Sándor et al.[14] simulated the soil temperature in Euro-Mediterranean grasslands based on uncertainties and ensemble performance. Breshears et al.[15] studied the effects of microclimate on soil water and heat in the woodlands of northern New Mexico, U.S., and they found that the solar radiation was the most important environmental factor affecting soil water and heat changes in forested areas. Dodds et al.[16] studied the impacting factors and dynamic process of soil temperature under conditions of film mulching, and their results showed that the average air temperature and solar radiation were the most important factors affecting soil temperature, followed by wind speed and relative humidity, with precipitation having the least impact; furthermore, the dynamic changes of the soil temperature were simulated. Shati et al.[17] studied the relationship among soil temperature (at depth of 5 cm) and snow depth, air temperature (at 2 m above the surface), and their results showed that there was a time-dependent, non-linear relationship between soil temperature (at depth of 5 cm) and air temperature (at 2 m above the surface) and the snow cover played a crucial role in the relationship. Beer et al.[18] studied the permafrost in the northern hemisphere, and based on meteorological data, the addition of external conditions, such as

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surface vegetation and snow coverage, was shown to improve the simulation and prediction accuracy of soil temperature changes in frozen-thawed soils. Michalska et al.[19] considered that the daily variation of soil temperature in shallow layers showed a continuously fluctuating trend, with good correlation with daily total solar radiation. With the increase of soil depth, the daily fluctuation trend of soil temperature gradually disappeared, and the correlation with daily total radiation decreased gradually. Therefore, soil temperature has a strong correlation with meteorological factors, but due to differences in soil freezing-thawing conditions and climate[20], certain differences exist in the correlation between soil temperature and meteorological factors, with strong regional characteristics therefore being exhibited. In the meantime, most of the previous studies focused on non-frozen-thawed soil, but the frozen-thawed process would change the soil structural composition and pore distribution, and the change of the soil structural composition made the influences of frozen soil and thawed soil on environmental temperature have great difference[21].

Therefore, to solve the above problems, taking the black soil area of Songnen Plain in Northeastern China as the research object, winter field experiments were carried out to measure the soil temperature at the tillage layer under four treatments (bare land, natural snowfall coverage, 5-cm-deep straw + natural snowfall coverage, and 10-cm-deep straw + natural snowfall coverage) during the freezing-thawing period. By means of correlation analysis, multiple regression analysis, and stepwise regression analysis, the dynamic simulation model between tillage-layer temperature and the environmental factors was constructed to reveal the dynamic changing pattern of the tillage-layer soil temperature during the freezing-thawing period and its relation with environmental factor.

2 Materials and methods

2.1 Description of study area

This study was carried out from November 2016 to April 2017 at the water-saving irrigation test site of Northeast Agricultural University, Harbin, Heilongjiang Province, China. The test site was located at 45°44'24"N, 126°43'7"E (as shown in Figure 1). It belongs to the temperate continental monsoon climate and has a long winter and short summer. During the study period, the minimum average daily temperature of –19.3°C occurred on January 12, the lowest temperature of –24.4°C occurred on December 27. The average temperature was –5.3°C, and the accumulated temperature was –23 008.9°C. The cumulative precipitation during the study period was 49.2 mm. The hardpan layer of approximately 20 cm was black soil, the 40-60 cm layer was clay-loess, and the layer below 60 cm was clay-black soil. The results of manual sampling showed that the average soil dry bulk density was 1.52 g/m^3, the saturated water content was 44.81%, and the field capacity was 32.73%. In addition, a Winner 801 laser particle size analyzer was used to determine the mechanical composition of the various soil particles[22], and the statistics showed that the percentage of clay (<0.002 mm) was 14.27%, the percentage of silt (0.002–0.02 mm) was 35.89%, and the percentage of sand (>0.02 mm) was 49.84% in soil.

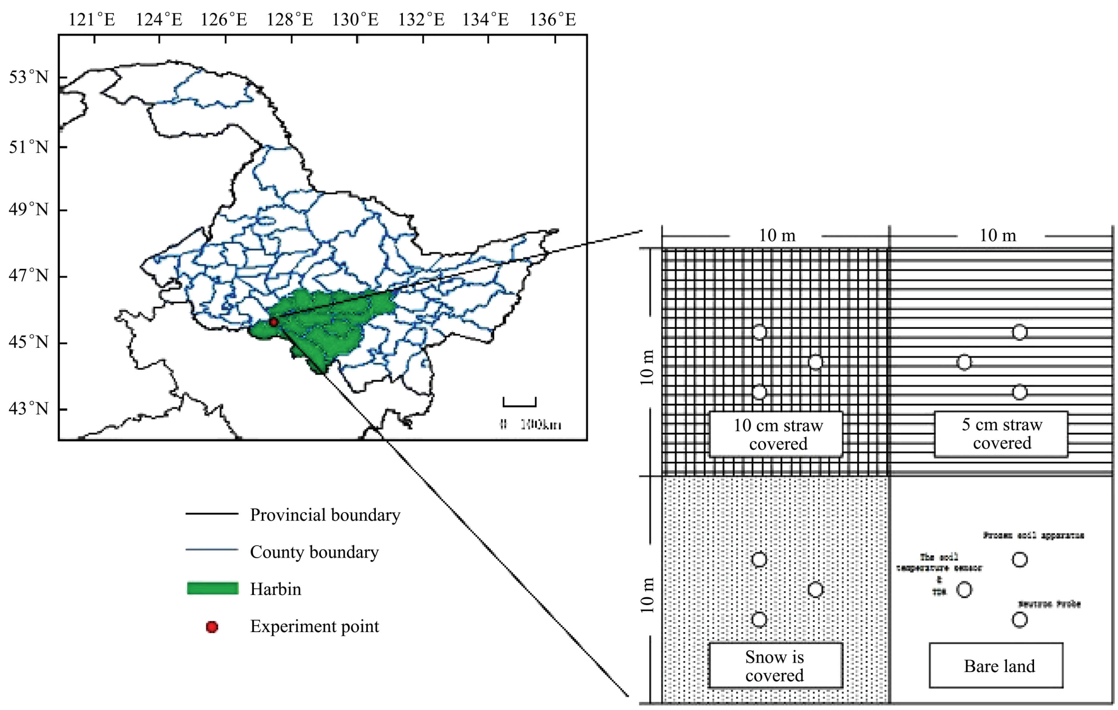


Figure 1 Location and settings of the study area

2.2 Experimental setup

The experimental site was divided into four areas, with 10 m × 10 m for each area. Four treatments were established, including bare land (BL), natural snowfall (NS), natural snowfall + 5-cm-deep straw coverage (6000 kg/hm^2; SC5), and natural snowfall + 10-cm-deep straw coverage (12 000 kg/hm^2; SC10). The straw used in this experiment was taken from the complete stem and leaf parts of field-grown corn plants harvested in 2016; straw was laid in a parallel manner for the SC5 treatment and was arranged in a crisscross pattern for the SC10 treatment. The BL treatment as the control was carried out by manual snow removal. During the study, a set of soil temperature monitoring equipment was installed in each plot to record soil temperature at the surface and at the soil depths of 10 cm, 20 cm, and 30 cm. The average soil temperatures at the depths of 10 cm, 20 cm, and 30 cm were taken as the soil temperature of the tillage layer, with the monitoring interval set at 1 h. The environmental factors of ambient temperature, ambient humidity, water vapor pressure, 10-min wind speed, total radiation, net radiation, and long wave radiation were recorded by the automatic weather station (PC-6, Jinzhou Yangguang, Liaoning, China) in the study site; the recording time interval was at 1 h.

2.3 Methods

To analyze the relation between the tillage-layer temperature and the environmental factors in frozen-thawed soils and to further simulate the dynamic process of the tillage-layer temperature, multiple regression analysis was used in combination with independent variable selection (i.e., stepwise regression method) to construct regression equations between the tillage-layer temperature and environmental factors for revealing the intrinsic relation between the environmental factors and the tillage-layer temperature. The data collected from 2016/11/01–2017/03/31 were used for fitting and for building multiple regression equations and stepwise regression equations. The data collected between 2017/04/01–2017/04/30 were reserved as test data to test the prediction accuracy of the models.

The tillage-layer temperature is represented by the dependent variable Y and assumes that p environmental factors affect the change of the tillage-layer temperature, namely, X_1, X_2, ... X_p. The model that uses these p environmental factors to fit the change of tillage-layer temperature is designated the full model[23,24]. Because the types of data counting unit and order of magnitude were different and easily cause the results to be unstable, the dimensional difference should be eliminated before building the full model. Therefore, the data were treated by the method of standardization treatment first, the calculation formulas are as follows:

$$y_j = \frac{Y_j - mean(Y)}{std(Y)},\ j = 1,2,...,132 \tag{1}$$

$$x_{ij} = \frac{x_{ij} - mean(X_{i.})}{std(X_{i.})},\ i = 1,2,...,p;\ j = 1,2,...,132 \tag{2}$$

where, Y is the tillage-layer temperature after standardization treatment; X is the environmental factor after standardization treatment; j is the serial number of the data; i is the serial number of environmental factor. Then the calculation formulas of building the full model are as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \mathrm{L}\ + \beta_p x_p + \varepsilon \tag{3}$$

By removing the environmental factor x_j from the p environmental factors, the resulting model uses (p-1) environmental factors to fit the tillage-layer temperature changes and is designated the reduced model, as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \mathrm{L}\ + \beta_{i-1} x_{i-1} + \beta_{i+1} x_{i+1} + \mathrm{L}\ \beta_p x_p + \varepsilon \tag{4}$$

The coefficient of multiple determination for the full model is R^2; the coefficient of multiple determination for the reduced model is denoted as R_j^2, and was defined as:

$$\Delta R_j^2 = R^2 - R_j^2 \tag{5}$$

Because the full model has one more environmental factor x_j, if ΔR_j^2 is almost zero, this value indicates that the addition of x_j will provide no significant improvement in explaining the tillage-layer temperature y; otherwise, the addition of x_j can provide a significant explanatory information for the regression model.

$$\text{Statistical assumptions} \quad \begin{matrix} H_0: & \Delta R_j^2 = 0 \\ H_1: & \Delta R_j^2 \neq 0 \end{matrix} \tag{6}$$

The test statistic is

$$F_j = \frac{\Delta R_j^2 / 1}{(1 - R^2) / n - p - 1} : \ F(1, n-p-1) \tag{7}$$

Equivalently, it can be written as

$$F_j = \frac{SSE - SSE_j}{MSE} \tag{8}$$

where, SSE_J is the sum of the squared residuals of the reduced model; SSE is the sum of the squared residuals of the full model; MSE is the mean square error of the full model.

Assuming that when the null hypothesis H_0 is true, F_j follows the F distribution. According to the test level α, the F distribution table (n_1=1, n_2=n–p–1) is referenced to obtain the cutoff value of the rejection region F_α. The decision criteria are as follows:

a) When F_j>F_α, this indicates that ΔR_j^2 is non-zero at the level of significance; that is, given that the environmental factors x_1, x_2, …, x_{j-1}, x_{j+1}, …, x_p have been included in the model, introducing the environmental factor x_j would significantly improve the explanatory ability of the tillage-layer temperature y.

b) When F_j≤F_α, this indicates that ΔR_j^2 is zero at the level of significance; that is, removing the environmental factor x_j from the full model would not impact the explanatory ability of the tillage-layer temperature y.

At the initial stage of this method, no variables were included in the model. The unitary linear regression model of the tillage-layer temperature y and each environmental factor was considered. All p models were subjected to the F-test, and the one with the highest F value was selected as the first environmental factor to be included in the model (denoted as x_{i1}).

Next, the remaining (p-1) environmental factors were respectively subjected to a partial F-test. If there existed at least one environmental factor x_i that passed the partial F-test, the one with the largest F_j was selected as the second independent variable to be included in the model (and denoted as x_{i2}). The above steps were repeated until all the environmental factors that were not included in the model failed to pass the partial F-test, at which time, the algorithm was terminated. Above calculation process was carried out by Matlab2010b.

3 Results and analysis

3.1 Correlation analysis of tillage-layer temperature and environmental factors

According to the results in previous studies[25], combined with the characteristics of the study area, a total of 10 variables—the soil surface temperature, ambient temperature, ambient humidity, water vapor pressure, 10-min wind speed, total radiation, net radiation, and long wave radiation—were chosen as environmental factors, and their correlations with the soil tillage-layer temperature were calculated, respectively. The specific results are shown in Table 1.

As can be seen in Table 1, each environmental factor has a good correlation with tillage-layer temperature, and the correlation was significant at the 0.01 level. Among them, the relation between the ambient humidity and the tillage-layer temperature was negatively correlated; that is, the tillage-layer temperature decreases with the increase in the ambient humidity. The relations between other environmental factors and the tillage-layer temperature are positively correlated. Across all four treatments, the soil surface temperature and tillage-layer temperature had the highest correlation coefficient, with an average correlation coefficient of up to 0.9305; the 10-min wind speed and tillage-layer temperature had the lowest correlation coefficient, with an average of only 0.3960. The other factors have a descending order of correlation coefficient with tillage-layer temperature as follows: ambient temperature > water vapor pressure > long wave radiation > total radiation > net radiation > ambient humidity. With the increase of coverage amount, the correlations between the five environmental factors (ambient temperature, total radiation, net radiation, long wave radiation, and soil surface temperature) and the tillage-layer temperature decreased gradually; the correlations between the other three environmental factors and the tillage-layer temperature did not change significantly. Compared with the relevant research, Fu et al.[26] reported that the relation between the ambient humidity and the tillage-layer temperature was positively correlated, which was completely opposite to results in this research, which may owe to the covers after thorough analysis. The former was snowfall, but the latter was snowfall+ straw in this paper. Different covers have different capacities of moisture absorption and then lead to the different effects on soil temperature.

Table 1 Correlation coefficients between environmental factors and the tillage-layer temperature

Treatment	Ambient temperature	Ambient humidity	Water vapor pressure	10-min wind speed	Total radiation	Net radiation	Long wave radiation	Soil surface temperature
BL	0.9376**	–0.5968**	0.8146**	0.3987**	0.7118**	0.6413**	0.8108**	0.9635**
NS	0.9028**	–0.6490**	0.7850**	0.4145**	0.7002**	0.6406**	0.7965**	0.9272**
SC5	0.9027**	–0.6059**	0.8179**	0.3921**	0.7090**	0.6502**	0.8059**	0.9400**
SC10	0.8580**	–0.5709**	0.7763**	0.3787**	0.6316**	0.5900**	0.7746**	0.8911**
Mean	0.9003	–0.6057	0.7985	0.3960	0.6882	0.6305	0.7970	0.9305

Note: * indicates $p<0.05$; ** indicates $p<0.01$. The same as below.

When two factors are correlated to the third factor at the same time, the correlation between the two environmental factors would inevitably be affected[27] and previous studies often ignored this point[12]. Therefore, to eliminate the impact of the third factor, only the correlation between the current environmental factors and the tillage-layer temperature were analyzed. The partial correlation coefficients of 8 environmental factors (including soil surface temperature, ambient temperature, ambient humidity, vapor pressure, 10-min wind speed, total radiation, net radiation, and long wave radiation) and the tillage-layer temperature were calculated. The specific results are shown in Table 2.

As can be seen in Table 2, after the impact of other environmental factors had been excluded, the correlation between each environmental factor and the tillage-layer temperature decreased significantly. Except for the soil surface temperature, ambient humidity, water vapor pressure, and certain individual environmental factors under some treatments, no correlations between the other environmental factors and the tillage-layer temperature were significant at the 0.01 level. Particularly for the 10-min wind speed, the absolute values of the partial correlation coefficients were all less than 0.08 under the four treatments. Across the four treatments, the partial correlation coefficient between soil surface temperature and tillage-layer temperature was the greatest, with the average as 0.5258; the partial correlation coefficient between long wave radiation and the tillage-layer temperature was the smallest, with an average of 0.022; the other environmental factors showed a descending order as follows: ambient temperature, total radiation, water vapor pressure, ambient humidity, net radiation, 10-min wind speed. With the increase in the coverage amount, only the correlation between the ambient humidity and the tillage-layer temperature gradually decreased, and the trends for correlations between the other seven environmental factors and the tillage-layer temperature were not obvious.

Hence, due to the large coupling effect among the environmental factors, a relatively large difference existed between the correlation analysis and the partial correlation analysis. This coupling effect not only changed the nature of the correlation between the environmental factors and the tillage-layer temperature (for example, the ambient temperature turned from a positive correlation to a negative correlation) but also reduced the degree of correlation between the environmental factors and the tillage-layer temperature. Additionally, the presence of coverage reduced the intensity of the heat exchange between the atmosphere and the soil, which further increased the complexity of the relation between environmental factors and the tillage-layer temperature.

Table 2 Partial correlations between environmental factors and the tillage-layer temperature

Treatment	Ambient temperature	Ambient humidity	Water vapor pressure	10-min wind speed	Total radiation	Net radiation	Long wave radiation	Soil surface temperature
BL	–0.179*	0.33	–0.224**	–0.064	–0.111	–0.164*	–0.17*	0.729**
NS	–0.151*	–0.27**	0.199**	–0.036	–0.133	–0.024	0.123	0.379**
SC5	–0.213**	–0.25**	0.294**	–0.006	–0.091	–0.043	0.118	0.553**
SC10	–0.104	–0.205**	0.189**	–0.071	–0.207**	–0.022	0.017	0.442**
Mean	–0.1618	–0.09875	0.1145	–0.04425	–0.1355	–0.06325	0.022	0.5258

3.2 Construction of dynamic simulation models for tillage-layer temperature

The above analysis showed that the impact of the environmental factors on the tillage-layer temperature of the soil varied, and there is a coupling effect to a certain degree. Therefore, to accurately simulate the dynamic process of the tillage-layer temperature and to eliminate the impact of the dimension, data for eight environmental factors and the tillage-layer temperature were first standardized, and multiple regression models for each treatment were then constructed. The results are shown in Table 3.

Table 3 Results of multiple regression analysis

Treatment	Multiple regression equation	R	F	$F_{0.01}$ (8,142)
BL	y_1=0.05–1.18x_1–0.024x_2–0.154x_3–0.035x_4–0.091x_5–0.057x_6–0.097x_7+2.571x_8	0.977	366.32	2.6389
NS	y_2=–0.218+0.538x_1+0.002x_2–0.11x_3–0.32x_4–0.086x_5–0.013x_6–0.078x_7+0.246x_8	0.920	97.77	
SC5	y_3=–0.157+0.425x_1+0.049x_2–0.171x_3–0.006x_4–0.049x_5–0.013x_6–00.057x_7+0.512x_8	0.940	134.38	
SC10	y_4=–0.174+0.732x_1+0.046x_2–0.343x_3–0.036x_4–0.208x_5–0.005x_6–0.095x_7+0.449x_8	0.850	46.17	

As can be seen in Table 3, the multiple regression equations for the tillage-layer temperature and each environmental factor under different coverage treatments were all significant at the 0.01 level, with the coefficient of multiple determination under the SC10 treatment being the smallest (the value was 0.85), and that under the BL treatment being the largest (the value was 0.977). Hence, the presence of coverage reduced the energy transfer between the environmental factors and tillage-layer soil, thereby contributing to the decreased significance of the multiple regression equations. By taking into account the actual situation, the more the environmental factors were used to simulate the tillage-layer temperature, the greater the work load of the experiment. Therefore, to reduce the number of environmental factors in the dynamic simulation of tillage-layer temperature while ensuring that the model could meet the simulation accuracy, the stepwise regression method was used to construct the dynamic simulation model for the tillage-layer temperature.

3.3 Construction of stepwise regression equations

According to Table 2, the environmental factors with the largest correlation coefficient under the four treatment conditions were respectively selected and included in the model in the first place. The specific results were as follows:

y_1=0.0329+1.0382x_8

(F=1061.206 R^2=0.8776 t_0=1.3662 t_1=32.576)

y_2= –0.2009+0.5545x_8

(F=504.9853 R^2=0.7733 t_0= –11.482 t_1=22.4719)

y_3= –0.148+0.6661x_8

(F=832.2621 R^2=0.849 t_0= –9.2865 t_1=28.8489)

y_4= –0.169+0.5796x_8

(F=203.285 R^2=0.5787 t_0= –6.15 t_1=14.2578)

Taking BL as an example: for y_1, which had a total of eight environmental factors, partial F-tests were conducted in turn by taking x_8 and y_1 as the reduced model and taking x_8 and y_1 plus any environmental factors from x_1, x_2, x_3, x_4, x_5, x_6 and x_7 as the full model. Among the variables that passed the F-test, the environmental factor x_j with the largest F_j was selected to form a new reduced model along with x_8; next, taking x_j, x_8, and T_1 as the full model, the remaining environmental factors were tested in turn. The above process was repeated until the F_j for each environmental factor in the full model was not significant, and the final standardized equation was obtained as follows:

y_1=0.0492–1.1484x_1–0.1633x_2–0.0773x_5–0.0606x_6–0.1126x_7+ 2.553x_8 (F=478.75, R^2=0.9526, R^2_{adj}=0.9506)

According to the above method, the stepwise regression results under the three treatments, NS, SC5, and SC10, were as follows:

y_2=–0.2202+0.42725x_1–0.0828x_5–0.099x_7+0.248x_8

(F=188.41, R^2=0.8386, R^2_{adj}=0.8342)

y_3=–0.1482+0.32364x_1–0.1283x_3–0.0634x_5+0.5118x_8

(F=264.13, R^2=0.8793, R^2_{adj}=0.876)

y_4=–0.1702+0.6677x_1–0.33x_3–0.047x_4–0.2064x_5+0.3948x_8

(F=72.66, R^2=0.7161, R^2_{adj}=0.7063)

The above results show that the stepwise regression equations of the tillage-layer temperature and environmental factors under the different treatments were different. Among them, the simulation equation of the tillage-layer temperature under the BL treatment had the greatest number of environmental factors, with six variables included in the model after variable selection. In contrast, only four, four, and five variables, respectively, were included in the models for the NS, CS5, and CS10 treatments. The covered therefore hindered the ability of some meteorological factors to impact the temperature change in the tillage-layer. With the increase of cover, the environmental factors affecting the tillage-layer temperature decreased gradually, which was consistent with the findings in literature [28].

3.4 Comparative analysis of the fitting accuracy for the tillage-layer temperature

To test the fitting accuracy of multiple regression models and stepwise regression models, scatter plots of the fitted values and the measured values of the tillage-layer temperature for the multiple regression models and stepwise regression models, respectively, were made, as shown in Figures 2 and 3.

As shown in Figure 2, the accuracies of the multiple regression models for the tillage-layer temperature under the four treatment conditions were all high, and the correlation coefficients between the fitted values and the measured values in the scatter plot were all significant at 0.01 level. Under the BL treatment, the correlation coefficient was especially significant, reaching 0.98. With the increase of the coverage amount and the correlation coefficient decreased gradually. The correlation coefficient under the SC10 treatment was the lowest, which was 0.85. These results further suggest that the presence of coverage increased the complexity of the tillage-layered temperature simulation. A comparative analysis of Figure 3 showed that the correlation coefficients between the fitted values of the stepwise regression equation for the tillage-layer temperature and the measured values in the scatter plot decreased under all four treatments, yet the decrease rates were small. For example, the correlation coefficient R under the BL treatment only decreased by 0.01 (decreased from 0.98 to 0.97), and the correlation coefficient R did not change under the SC5 treatment. Thus, upon stepwise regression, although the number of environmental factors in the models had been reduced, the fitting accuracies of the models did not decrease significantly.

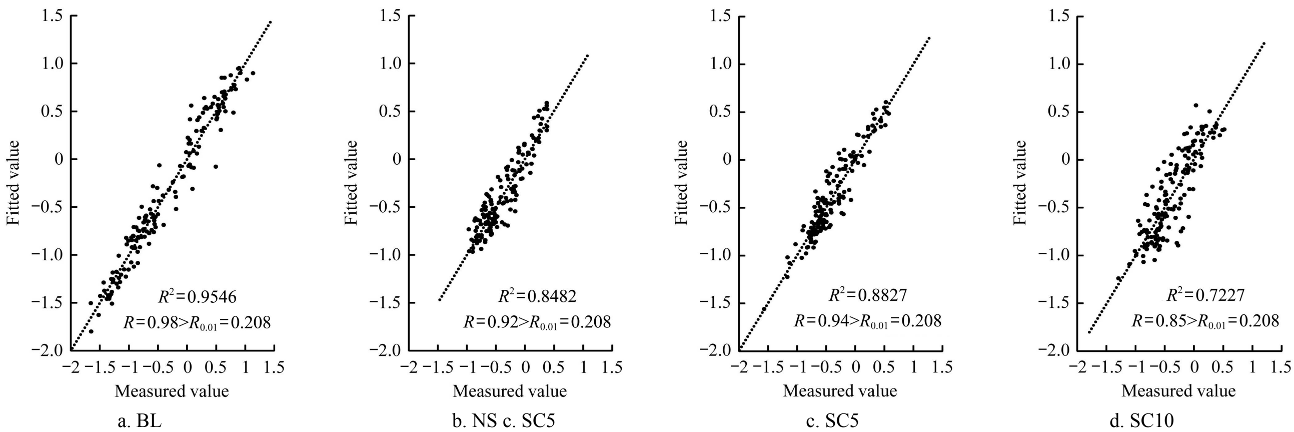
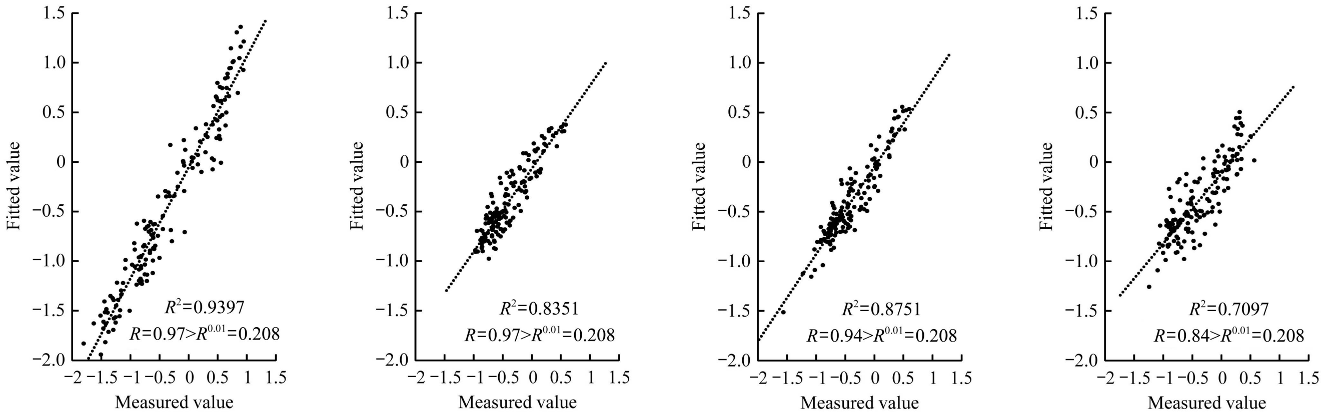


Figure 2 Fitting accuracy test of multiple regression models for the tillage-layer temperature

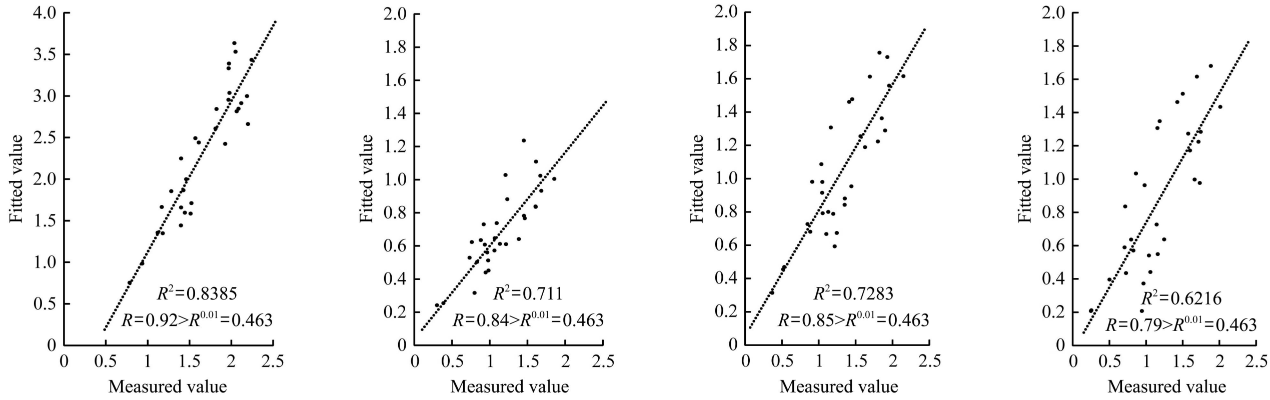


a. BL b. NS c. SC5 d. SC10

Figure 3 Fitting accuracy test of stepwise regression models for the tillage-layer temperature

3.5 Test of the prediction results

Using the above stepwise regression models, predictions were made using the data from the period 2017/04/01–2017/04/31 under the four treatments, which were then compared with the measured data by graphing scatter plots (Figure 4). As shown in Figure 4, in the prediction stage, the correlation coefficient under the SC10 treatment was the smallest, indicating the lowest prediction accuracy. The correlation coefficient under the BL treatment was the highest, indicating the highest prediction accuracy. However, the correlation coefficients between the predicted values and the measured values of the tillage-layer temperature under the four treatments were all significant at 0.01 level. In other words, the constructed stepwise regression models for the tillage-layer temperature are accurate and can meet the needs of simulating tillage-layer temperature under the different conditions.



a. BL b. NS c. SC5 d. SC10

Figure 4 Prediction accuracy test for stepwise regression models of tillage-layer temperature

4 Conclusions

Soil temperature is an important parameter to regulate soil moisture content. Its variation process influences the balance of soil energy budget to some extent and determines the effect of soil energy storage and moisture conservation. To improve the utilization efficiency of agricultural soil and water resources and enhance the forecast and regulation ability of soil moisture content to ensure the efficient and stable yield of crops, through observation of the tillage-layer soil temperature and meteorological data in different mulching treatment conditions in Harbin area in winter as well as the correlation analysis and partial correlation analysis, the paper has calculated the effects of various meteorological and environmental factors on the tillage-layer soil temperature and screened the meteorological factors by multiple regression analysis and stepwise regression analysis. Compared with other studies, parameters of the simplified soil temperature prediction model had not been screened to reduce the observation requirements of meteorological factors in the process of soil temperature prediction. Since the test site is located in Harbin, Heilongjiang Province, the climate belongs to the continental monsoon climate in the mid-temperate zone and the soil is black soil, the test results have certain regional limitations. Parameters in the paper shall be adjusted appropriately according to the regional conditions when carrying out temperature simulation calculation in other regions. The main conclusions are as follows:

(1) The simple correlation analysis was quite different from the partial correlation analysis in terms of the relation between tillage-layer temperature and environmental factors. The coupling effects between environmental factors not only changed the nature of the correlation between the environmental factors and the tillage-layer temperature but also reduced the degree of correlation between the environmental factors and the tillage-layer temperature. The presence of coverings weakened the intensity of the heat exchange between the atmosphere and the soil, which further increased the complexity of the relation between the environmental factors and the tillage-layer temperature.

(2) Compared with the results of the multiple regression models, the numbers of environmental factors used to construct the stepwise regression models decreased by 25%, 50%, 50%, and 37.5% under BL, NS, SC5, and SC10, respectively. This decrease in the environmental factors greatly reduced the experimental

workload and provided a new means for the prediction of tillage-layer temperature.

(3) Some differences existed in the stepwise regression models for the tillage-layer temperature under the different coverage conditions. The larger the coverage amount, the fewer the environmental factors that could affect the tillage-layer temperature. The coefficients of determination of the dynamic prediction for tillage-layer soil temperature under the four treatments (BL, NS, SC5, and SC10) were 0.8385, 0.7110, 0.7283, and 0.6216, respectively. The prediction accuracy was high and could accurately characterize the dynamic changes of the tillage-layer soil temperature. These results provided an important theoretical basis for the efficient utilization of farmland soil water and heat resources.

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