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An empirical and a dynamic-empirical model for the estimation of maize seedbed temperature

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Abstract— Soil temperature is the main factor in determining the germination of maize seeds and the emergence time of the crop. It controls the rate of phenological development while the meristem is underground, which is until the V6 (six leaf collar) stage of maize. The research performed by the authors aimed to model maize seedbed temperatures at sowing depth (soil temperature at 5 cm depth) during the sowing-emergence-early development period. The research is based on measurements in ploughed plots of the maize experiments at the Látókép Experiment Site of the University of Debrecen (Eastern Hungary) in two growing seasons of 2021–2022. Two types of empirical models were established, a multilinear regression model (M1) and a dynamic-empirical model (M2), where the daily increase and decrease of soil temperature are determined by multilinear regression. Candidates for input variables for both models were various, easily available daily meteorological parameters. M2 model performed better than M1 when applied to an independent database of 2022. This is particularly valid for the maximum and minimum soil temperatures. It was found that both M1 and M2 can be used to predict the soil temperature of the maize seedbed before shading by the plants. For daily mean temperature, M1 and M2 give a similarly good estimation, while the dynamic-empirical model has to be preferred for the maximum and minimum temperatures. M2, which is based on daily temperature, global radiation and wind speed data, predicts the daily mean (RMSE = 1.4 °C), maximum (RMSE = 2.2 °C), and minimum (RMSE = 1.6 °C) of seedbed temperature not worse than many earlier soil temperature models do, even hybrid or mechanistic ones with a large number of parameters.

Key-words: soil temperature, dynamic-empirical model, seedbed, maize, linear regression

1. Introduction

Soil temperature has an important role in crop production. It is the main factor in determining the germination of maize seeds and the emergence time of the crop (*Stone et al.*, 1998; *Santos et al.*, 2019). Soil temperature controls the rate of phenological development while the meristem is underground, which is until six leaves fully expand (V6 stage) or the tip of the 10th leaf appears (*Stone et al.*, 1999). The results of field experiments with soil cover (nearly identical air temperatures and significantly different soil temperatures) demonstrate this effect (*Lu et al.*, 2020). At higher soil temperatures, the faster initial development results in a shorter growing season and significantly earlier flowering and physiological maturation (*Stone et al.*, 1998). In maize (*Bollero et al.*, 1996) and other crops (*Jamieson et al.*, 1995), it is often more effective to calculate the length of early developmental stages using soil temperature rather than air temperature. However, when there are no different soil temperature "treatments", soil temperature-based thermal unit models do not perform better than air temperature-based models as found out by *McMaster* and *Wilhelm* (1998). Soil temperature directly or indirectly affects various physical, chemical and biological processes in the soil. From the perspective of practical maize production, other important processes that are affected by soil temperature include root growth (*Xia et al*., 2021), phenological development of maize pests (*Streda et al.,* 2013), and water and nutrient uptake by roots (*Ni et al.,* 2019).

At weather stations, soil temperatures are typically measured under bare surface, sometimes under grass. According to WMO standards, a bare (uncovered) area of approximately 2 m × 2 m should be designated for measuring soil temperature at synoptic and climate stations (*WMO*, 2018). The Hungarian Meteorological Service recommends that measurements should be taken in an area of at least 1 m^2, kept permanently free of weeds. For agricultural weather stations, two types of standard cover are used – bare soil and short grass. Wherever possible, simultaneous readings should be made under both standards for comparison (*WMO*, 2012).

Under field conditions, the temperature conditions are different from both bare and grass covered soils. Significant differences can occur in the radiative balance of the soil surface and in the magnitude of sensible and latent heat fluxes. The soil structure due to tillage is also different from the basically undisturbed soil structure of the weather stations, causing differences in the soil thermal properties and in its temperature conditions. Tillage typically increases soil temperature in the upper layers, which can be observed even under strip tillage (*Cox et al.*, 1990; *Licht* and *Al-Kaisi*, 2005; *Ozpinar* and *Ozpinar*, 2015). Soil thermal properties are spatially highly variable, mainly due to heterogeneity in moisture content and compaction (*Usowicz et al.*, 1996). Heat capacity increases linearly with soil moisture and is significantly less sensitive to soil volumetric mass. Thermal conductivity also increases with soil moisture, although at a decreasing rate. Soil thermal properties are sensitive to changes in soil compaction, especially in the less compacted range (*Abu-Hamdeh* and *Reeder*, 2000).

Soil temperature is determined by a combination of meteorological factors, soil thermal properties, and certain crop parameters. These (or a subset of them) can be used to calculate soil temperature, and mechanistic, empirical, and hybrid models combining the two can be used in practice. Mechanistic models describe the physical processes that determine soil temperature, whose main elements are the surface energy balance, with components such as the radiative balance, latent and sensible heat fluxes in the air, and molecular heat conduction in the soil. These models should be run preferably with site-specific input data combined with hydrological or plant simulation models to maximize the potential of the sophisticated method. Complex simulation models including soil temperature modules such as APSIM (*Keating et al.*, 2003; *Chauhan et al.*, 2007; *Archontoulis et al.*, 2014), DSSAT (*Jones et al.*, 2003) can be used effectively for calculating soil temperature of arable crops. Soil thermal and water retention conditions including plant cover are modeled by the CoupModel (*Liu et al.*, 2022), AGRISOTES (*Grabenweger et al.,* 2021), SiSPAT (*Brauda et al.*, 1995; *Ji et al.*, 2009), and HYDRUS-1D models (*Simunek et al.*, 2008).

Empirical models are based on statistical relationships between soil temperature and various meteorological and soil parameters. In many cases, they provide a reasonable accuracy for practical applications using only a few basic meteorological variables. The surface energy balance is the main determinant of both air and soil temperatures, so they are closely related. *Günes et al.* (2014) modeled daily air temperature data for different soil types at a depth of 5 cm below the grass surface using non-linear empirical relationships depending on the saturated/unsaturated state of the soil. *Barman et al.*, (2017) estimated soil temperature values at 5, 15, and 30 cm below bare soil surface using regression analysis. For morning soil temperature, the best prediction was obtained using the nonlinear functions of daily mean temperature and for afternoon soil temperature (in the upper layers) with daily maximum air temperature. Examining many years of soil temperature data obtained by the weather stations, it was found that the correlation with air temperature decreases with depth, with the highest correlation for 5 and 10 cm (*Islam et al.*, 2015). Backward reconstruction of soil temperature below forest canopy was successfully achieved using regression equations based on air temperature data (*Brown et al.*, 2000). On a continental scale, a sufficiently accurate estimate of soil temperature can be obtained using a shifting average of daily precipitation sum and air temperature (*Zheng et al.*, 1993). The base model is valid for bare soil, while the effect of plant cover was described in the model using the leaf area index. *Perreault et al.* (2013) modeled soil temperature under maize stands at depths of 10, 25, and 50 cm with soil texture, daily maximum and minimum temperatures, and daily precipitation data as inputs. Their results were used to study weed germination and emergence. In estimating daily soil temperature, *Delbari et al.* (2019) found the performance of a support vector regression (SVR) based model and the more classical multilinear regression models (MLR) similarly favorable for the 10-cm layer. In estimating soil temperature at deeper layers, SVR performed better than MLR. The empirical soil temperature models are essentially site-specific (*Langat*, 2021) and valid under the given climatic and soil conditions and agrotechnology.

The base temperature of maize is typically between 7–10 °C (*Gilmore* and *Rogers*, 1958; *Narwal et al.*, 1986; *Birch et al.*, 1998; *Tsimba et al.*, 2013). According to practical recommendations, maize should be sown when soil temperature is permanently above the base temperature. The course of spring soil temperatures, the actual and forecast values, is very important agrometeorological information needed by growers because of its direct practical use. Although measured and predicted soil temperature data are available, they are not sufficiently specific and do not characterize seedbed temperature conditions properly.

This research aimed to develop a soil temperature model that calculates maize seedbed temperatures at sowing depth (soil temperature at 5 cm depth) during the sowing-emergence-early development period. It was important to use only easily available daily meteorological data and to reach an accuracy suitable for practice.

2. Material and methods

The performed research is based on measurements taken in Eastern Hungary at the Látókép Experiment Site of the University of Debrecen (N 47°33', E 21°27', 120 m asl). The soil of the area is mid-heavy calcareous chernozem with a physical type of loam, and Arany's plasticity index of 39. The soil is characterized by excellent hydrophysical properties and high yield potential. The soil temperature measurements were set up in ploughed plots of the maize experiments (multifactoral long-term field experiment and sowing time experiment) in two growing seasons of 2021-2022. Following the typical soil cultivation practice, the experimental plots were ploughed in the months of October-November prior to the growing season at a depth of 30 cm. Basal fertilizer was applied at the rates of 80 kg N ha^{-1}, 60 kg P_2O_5 ha^{-1}, and 90 kg K_2O ha^{-1}. After winter, the first soil cultivation (field rolling) was performed in March, when soil moisture conditions became favorable. Seedbed preparation was done within a few days before sowing. Maize (Merida FAO 380) was sown at a density of 80,000 plants ha^{-1}, with 0.76 m row spacing. Sowing depth was 5-6 cm. Interrow cultivation was performed only after the trial period.

2.1. Soil temperature measurements

Soil temperature measurements were carried out using HOBO UA-002 temperature data loggers. All thermologgers were preliminary tested with parallel measurements in stable, homogeneous indoor circumstances. The average temperature of the 24-hour period was calculated from 10-minute measurements for each device. These values showed very small differences (maximal difference from the total mean did not exceed 0.3 °C). However, a correction value was determined and applied for each device according to the obtained test results. The thermometers were installed in each parcel within a few days after sowing. Measurements covered most of the growing season, but only data of up to 30 days after sowing was used according to the purpose of the research, when the shading effect of the emerged maize was still negligible (*Table 1*). Two plots with different sowing date were used in the research in order to have a longer measurement period for modeling. For both years, the first part of the soil temperature dataset used in modeling originates from the first sown plot of the sowing date experiment performed in maize. The second part of the dataset is based on the measurements in the multifactorial long-term experiment, where maize was sown 3–4 weeks later.

Table 1. Timing of the soil temperature measurement program in 2021–2022 and the related crop data

year	**examination period**	**date**			
		sowing	**installation of thermologgers**	**emergence**	**V6**
2021	April 1–27	March 31	March 31	April 27	May 25
	April 28 – May 22	April 22	April 27	May 6	June 3
2022	April 8 – May 3	April 6	April 7	April 28	May 23
	May 4 – June 1	May 2	May 3	May 9	May 31

The thermometers were placed exactly in the rows at a depth of 5 cm, in four replicates in 2021. In 2022, there was a possibility for only three replicates, because of the changes in the complex soil temperature research program (aiming at the effect of depth and tillage). While installing the thermologgers, we focused to regenerate the original soil surface and compaction conditions of the seedbed.

The daily mean, minimum, and maximum temperature values were determined from data recorded at 10-minute intervals. Using 0–24 hour observing window in search for minimum/maximum temperature often omits the true temperature extrema, and instead identifies endpoint temperatures. The capturing of true "peaks and lows" of diurnal temperature cycle can be improved by recording maximum and minimum values at the coldest and warmest time of day, respectively (*Rischard et al.*, 2018). Another possibility is the identification of temperature extrema within continuous nighttime and daytime intervals (*Zaknic-Catovic* and *Gough*, 2022). Adapting this night-and-day climatological observing window for our soil temperature model, the daily minimum values were calculated on the 0–14 CET time intervals and the maximum values on the 12–02 CET time intervals.

2.2. Meteorological measurements

Air temperature and humidity measurements were taken at 2 m height, at 10-minute intervals, in a distance of 500 m from the experimental area, above a short-cut grass surface. Microsoft Excel was used to determine the daily data for statistical analyses. Precipitation was measured using a conventional Hellmann rain gauge and an automatic weighing gauge in parallel. The data from the latter were used to characterize the rainfall patterns of the study periods.

The wind speed (10 m) and global radiation data measured at the Debrecen-Kismacs station of the Hungarian Meteorological Service (OMSZ, 2022) were used for the analysis. Considering the number of factors (distance of 10 km, similar agricultural area, high accuracy measurements, spatial heterogeneity), this solution is acceptable.

2.3. Soil temperature model

The aim of this research was to create an empirical model for estimating daily soil temperature values. According to the data requirements of the different thermal time methods, the determination of daily minimum and maximum values in addition to the daily mean temperature was part of the calculations. The research focused only on the period of sowing-emergence-early development, when the soil temperature information is especially needed by maize growers in practice. The two model versions were not aimed to be extended to the later phenological phases, therefore, the shading effect of the vegetation was not included. Data from 2021 was used for model calibration, while validation was based on 2022 data.

In Model 1 (M1), the following meteorological parameters were included in the multilinear regression analysis (stepwise regression, SPSS Statistics 27.0): daily average temperature (TA_{ave}, °C), daily minimum temperature (TA_{min}, °C), daily maximum temperature (TA_{max}, °C), daily global radiation (G, MJ m^{-1}), daily average wind speed (w, ms^{-1}), and mean temperature of the preceding 1-, 2-, 3-, 4-, 5-, 6-, and 7-day-period.

The study also included a specific dynamic-empirical model (Model 2, M2), which has the same base as a previous model describing the temperature of the rice floodplain (*Gombos*, 2008). The model treats the warming and cooling phases of the daily soil temperature cycle separately, and determines the nighttime temperature decrease ($\Delta T1$) and daytime temperature increase ($\Delta T2$) of the soil for each day (*n* is the day of the simulation) based on empirical relationships. Steps:

1. Setting the maximum soil temperature for the previous day of the study period, with estimated or measured initial value ($TS_{max,0}$);
2. Determination of the night-time decrease in soil temperature based on meteorological data (and soil temperature) using an empirical formula ($\Delta T1_n$)
3. Calculation of the minimum soil temperature: $TS_{min,n} = TS_{max,n-1} - \Delta T1_n$;
4. Calculation of the daytime increase in soil temperature using an empirical formula: ($\Delta T2_n$);
5. Calculation of daily maximum soil temperature by adding the increase to the minimum: $TS_{max,n} = TS_{min,n} + \Delta T2_n$.

Repeating steps 2 to 5 N times, the minimum and maximum soil temperature is obtained for each day of the period under study (*N* is the number of days).

The empirical formulas estimating $\Delta T1$ and $\Delta T2$ were determined also in this case using multivariate linear regression analysis. Compared to the M1 model, the set of initial parameters differed:

- the mean temperature of the preceding 1, 2, ..., 7-day periods was omitted,
- the parameter *CF* representing the cooling effect of air was included: $CF_n = TS_{max,n-1} - TA_{min,n}$,
- and *WF* representing the heating effect of air was calculated $WF_n = TA_{max,n} - TS_{min,n}$.

The idea for the introduction of the new parameters is based on the assumption that the greater the values of *CF* (the difference of the minimum air temperature and the previous day's soil temperature maximum) are, the higher the decrease in soil temperature is. The introduction of the *WF* variable can be explained similarly. An increase in model stability is also expected by defining new variables in this way, as it provides negative feedback.

2.4. Model validation

Model calibration and regression coefficients were determined using data from 2021 (52 days) and validated with data from 2022 (55 days). The comparison of the estimated (P_i) and actual (O_i) daily minimum, maximum, and mean soil temperature values was compared graphically first. As a next step, to objectively evaluate the performance of the model, the commonly used statistical indices were applied (n is the number of days). These statistics focus on different aspects of model performance:

- The coefficient of determination (*CD*) shows how closely the estimated data follow the trend of the measured values. Values close to 1 indicate that the model is optimal in this aspect.
- Root mean square error (*RMSE*) quantifies the deviation between estimates and observations according to this formula:

$$RMSE = \sqrt{\frac{\sum(P_i - O_i)^2}{n}} \,. \tag{1}$$

- Model efficiency (*EF*), the optimum of this coefficient is 1, if positive, the model is a better predictor than the average of measured values:

$$EF = 1 - \frac{\sum(P_i - O_i)^2}{\sum(O_i - \bar{O})^2} \,. \tag{2}$$

- Mean absolute error (*MAE*) provides a measure of error based on the absolute value of the deviations:

$$MAE = \frac{|P_i - O_i|}{n} \,. \tag{3}$$

- Mean error (*ME*) or bias shows whether and to what extent the model over or underestimates the measured values in average:

$$ME = \frac{P_i - O_i}{n} \,. \tag{4}$$

In addition to the real daily mean temperature, a value calculated from the average of the maximum and minimum can also be important (many models calculate daily thermal units based on the latter). The M1 model gives a separate estimate for both, while for M2, both parameters can be estimated with the same value ($TS_{nx/2}$).

3. Results

3.1. Weather conditions

Both the calibration (2021) and validation (2022) periods greatly overlapped with the time period April-May.

The weather in April 2021 was poor in sunshine and significantly cooler than the long-term average. There were several occasions of light precipitation, but the total monthly rainfall was only half the long-term average (*Fig. 1*). In May, the weather was cooler than normal for this time of year, with near average rainfall and sunshine duration. April 2022 was also cool with less hours than average, but with more rainfall than in the previous year. The weather in May was the opposite as in 2021, with above-average temperature, more sunshine, and small amount of precipitation. It can be concluded that the weather conditions in the calibration and validation periods differed significantly, especially in May.

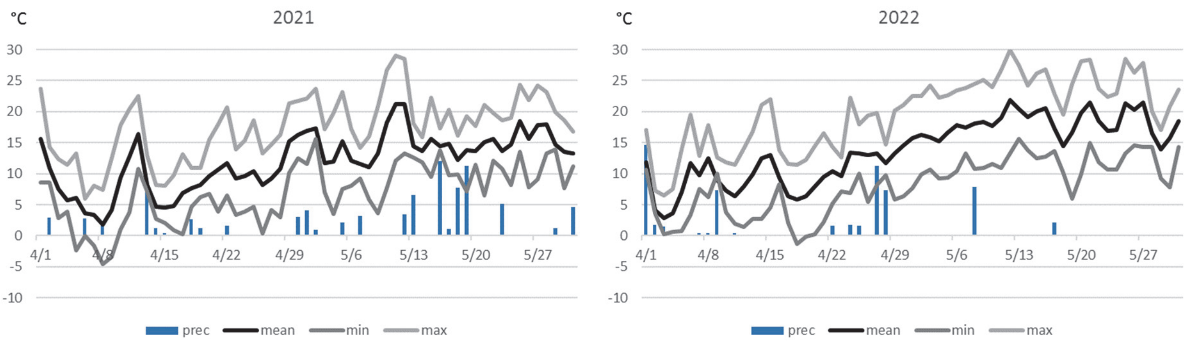

Fig. 1. Daily values of precipitation and mean, minimum, and maximum temperatures in the period of April to May in 2021 and 2022.

3.2. Calibration

3.2.1. Model 1

In our multilinear regression model (M1) for estimating the daily mean soil temperature (TS_{ave}), the final formula obtained using the stepwise method includes the daily mean air temperature (TA_{ave}), mean temperature of the previous 7 days (TA_7), and global radiation (G) as independent variables. The model was not significantly improved by wind speed, relative humidity, daily minimum and maximum temperatures.

$$TS_{ave} = 0.660 \cdot TA_{ave} + 0.329 \cdot TA_7 + 0.102 \cdot G + 0.74 \, . \qquad (5)$$

For daily minimum soil temperature (TS_{min}), the parameter of greatest weight is the minimum air temperature (TA_{min}), the other important parameter is the mean temperature of the previous day (TA_1). Logically, the daily global radiation has no effect due to the time lag. This explains why no daily mean value of any meteorological element appears in the formula.

$$TS_{min} = 0.455 \cdot TA_{min} + 0.346 \cdot TA_1 + 2.82 \,. \quad (6)$$

The regression calculation for the daily maximum of soil temperature (TS_{max}) also confirmed the preliminary expectations. The daily maximum (TA_{max}), mean and global radiation (G) of air temperature are included in the formula. Temperature averages on previous days are also correlated with the soil temperature maximum, with significant improvements in the model obtained by including the 4-day mean temperature (TA_4) as an independent variable. The regression equation is as follows:

$$TS_{max} = 0.397 \cdot G - 0.147 \cdot TA_{max} + 0.808 \cdot TA_{ave} + 0.172 \cdot TA_4 + 2.82 \,. \quad (7)$$

For the calibration period, the following were found (*Table 2*):

- The coefficient of determination and the model efficiency have high values ($R^2 = 0.95 – 0.96$, $EF = 0.94 – 0.96$), almost equal for all variables.
- The average error, which refers to the systematic error, is very small, with an underestimation of 0.2°C only for the minima.
- The root mean square error and the mean absolute error are the largest for daily maxima and the smallest for daily mean temperature.

There is no significant difference in the estimates of the two different daily means.

Table 2. M1 model performance on the calibration (2021) data set

M1	*RMSE*	*MAE*	*ME*	R^2	*EF*
minimum	0.9	0.7	-0.2	0.95	0.94
maximum	1.2	1.0	0.0	0.95	0.95
average	0.9	0.7	0.0	0.95	0.95
(max+min)/2	0.8	0.7	-0.1	0.96	0.96

3.2.2. Model 2

In the dynamic-empirical model (M2), multivariate linear regression was used to describe the daily cooling and warming phases of the soil and its temperature changes. The nighttime soil temperature decrease ($\Delta T1$) showed the strongest correlation with the variable *CF*, which can be interpreted as the cooling effect of air.

The inclusion of the air temperature minimum significantly improved the prediction. The regression equation is as follows:

$$\Delta T1 = 0.725 \cdot CF + 0.190 \cdot AT_{min} - 1.37 \ . \qquad (8)$$

The increase in soil temperature during the day ($\Delta T1$) is estimated using a regression equation with daily global irradiance, daily mean wind speed, and the warming effect of air (WF) as independent variables:

$$\Delta T2 = 0.392 \cdot G - 0.844 \cdot w + 0.229 \cdot WF + 2.69 \ . \qquad (9)$$

From the values of $\Delta T1$ and $\Delta T2$ calculated for each day, the daily minimum and maximum of the soil temperature for the whole calibration period are obtained by successive subtraction and addition, respectively. By taking the simple arithmetic mean of these extremes, the daily mean temperature can be calculated.

While the M1 model is based on a direct empirical estimation of daily soil temperature values (min, max, mean), in the dynamic-empirical model, the soil temperature data are obtained indirectly after a multi-step calculation. Therefore, as expected, the estimation error of the M2 model on the calibration database is larger than that of the M1 model (*Table 3*). Further findings on the performance of the M2 model are:

- The largest error, as for M1, is in the predictions of daily maximum soil temperature ($RMSE$ = 1.7 °C, MAE = 1.4 °C).
- The $RMSE$ and MAE for minimum temperature are slightly smaller than for mean temperature.
- The values of the coefficient of determination (R^2 = 0.94 – 0.97) show no difference compared to M1, but the model efficiency is lower (EF = 0.86 – 0.90).
- The systematic error is negligible for the maxima and minima and, as a result, also for their mean. The actual daily mean differs from the latter (it is lower), resulting in an average overestimation of 0.4 °C.

Table 3. M2 model performance on calibration (2021) data set

M1	*RMSE*	*MAE*	*ME*	R^2	*EF*
minimum	1.4	1.1	0.0	0.97	0.87
maximum	1.7	1.4	0.0	0.94	0.90
average	1.6	1.3	0.4	0.95	0.86
(max+min)/2	1.5	1.2	0.0	0.96	0.87

3.3. *Validation*

Indices for the evaluation of the models were calculated using the independent validation data of 2022. It is normal that the performance of empirical models is weaker for a new independent data set than for the calibration period. This is clearly the case for the M1 model (*Table 4*):

- Especially in the estimation of the temperature extremes, there is a large loss in accuracy.
- The M1 model is the most inaccurate in predicting the maximum soil temperature, followed by minimum temperature. The regressed maxima (2.0 °C) and minima (1.4 °C) are lower than the measured values averaged over the 52 days.
- These errors for mean temperature are significantly smaller (*RMSE* = 1.5 °C, *MAE* = 1.2 °C, *ME* = -0.9 °C).
- The model efficiency is below 0.8 for the extreme value estimate, but above 0.9 for the daily average.
- The mean calculated by averaging the estimated extremes is significantly less suitable to estimate the real daily mean than the direct (applied to the daily mean) empirical relationship.

The majority of the indices show an advantage of the M2 model over the M1 (except for the coefficient of determination for the daily mean temperature), (*Table 4*):

- Its advantage over M1 is the largest for the minimum temperature, but also significant for daily maximum values and for the mean temperature calculated from extreme values.
- The performance of M2 is also the weakest (in all indices) in prediction of the daily maximum soil temperature and the best for daily mean temperature.
- It should be noted that the dynamic-empirical model estimates the daily mean temperature on the validation dataset with smaller errors (*RMSE*, *MAE, ME*) compared to the calibration dataset.

Table 4. M1 and M2 model performance on the validation (2022) data set

M1	*RMSE*	*MAE*	*ME*	R^2	*EF*
minimum	2.6	2.2	-1.4	0.91	0.76
maximum	2.7	2.3	-2.0	0.89	0.76
average	1.5	1.2	-0.9	0.96	0.92
(max+min)/2	2.3	2.0	-1.7	0.94	0.80
M2	*RMSE*	*MAE*	*ME*	*R2*	*EF*
minimum	1.6	1.2	-0.4	0.92	0.91
maximum	2.2	1.7	-1.3	0.92	0.84
average	1.4	1.0	-0.3	0.93	0.93
(max+min)/2	1.5	1.1	-0.8	0.95	0.91

Fig. 2 shows the measured daily mean soil temperature and the values calculated by the two model versions. M1 reproduces the real values very well over the whole calibration period. The M2 model showed an underestimation of more than 2°C for the period April 6-8, 2021 (*Fig. 2*). During the last days of major warming events, M2 tends to overestimate the soil temperature (above 2 °C: April 12, April 29 – May 2). In the 2022 validation period, M1 prediction is below the daily mean from the measured data on most days. However, the deviations exceed 2 °C only on a few days at the end of May. The M2 model gives a very accurate prediction for most of the period, but there are some critical periods when the error is larger than that of the M1 model. On 7 days, which is 13% of the total number of days in the study period, the prediction error (absolute value) is larger than 2 °C, which is reasonable compared to the results of other studies. *Zheng et al*. (1993) found in average 40% of days with larger than 2 °C error in their empirical model for soil temperature at 10 cm.

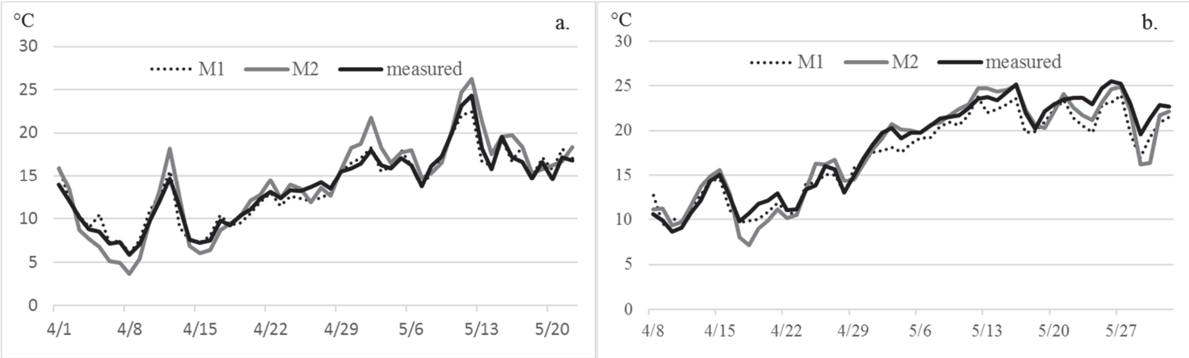

Fig. 2. Daily mean soil temperature values estimated by M1 and M2 models and the daily average of the measured (in every 10 minutes) soil temperature data. (a) Calibration period (April 1 -May 22, 2021), (b) validation period (April 28 -June 1, 2022).

4. Conclusions

The research described in this paper has shown that maize seedbed temperature can be estimated using multilinear regression with high accuracy over the calibration period. For the minimum temperature, it is sufficient to use various air temperature data as input, while the addition of global radiation in the regression estimation of the daily mean and maximum leads to a significant improvement. For the daily mean soil temperature, the classical empirical model (M1) fits very well (*RMSE* = 0.9 °C, *MAE* = 0.7 °C, *ME* = 0.0 °C, *R2* = 0.95, *EF* = 0.95).

However, validation on an independent database gives a more realistic indication of model applicability. A common way is to divide the test period into two parts to define the calibration and validation databases. The outlined research followed this approach, and it was found that the model performance had become weaker. The mean temperature estimate still remained favorable when compared with literature data. The *RMSE* of 1.5 °C is acceptable, because the maize seedbed at 5 cm depth is more directly exposed to weather than the soil at greater depths and under vegetated surface.

The dynamic-empirical (M2) model performed well on the calibration database, but underperformed the classical empirical model. The explanation for this difference is that M2 calculates the daily maximum and minimum values indirectly, with daily steps up and down in the soil temperature. However, as in a previous similar study on rice flooding water (*Gombos*, 2008), the M2 model performed better than M1 when applied to an independent database. This is particularly valid for the maximum and minimum soil temperatures. In the prediction of daily mean temperature, M2 even improved slightly compared to the calibration period. Overall, M2, which is based on daily temperature, global radiation and wind speed data, calculates the daily mean (*RMSE* = 1.4 °C), maximum (*RMSE* = 2.2 °C) and minimum (*RMSE* = 1.6 °C) of seedbed temperature with the accuracy expected. These values of *RMSE* and also the coefficients of determination (0.92–0.93) are in the same range as or better than in the case of many earlier soil temperature models, even hybrid or mechanistic ones with a large number of parameters (*Roloff et al.,* 1998; *Kang et al.,* 2000; *Sándor* and *Fodor,* 2012; *Liu et al.,* 2013; *Perreault et al.,* 2013). It can be concluded that both M1 and M2 can be used to predict the soil temperature of the maize seedbed before shading of the plants. For daily mean temperature, M1 and M2 provide a similarly good estimation, while the dynamic-empirical model has to be preferred for the maximum and minimum temperatures. However, the results must be used with appropriate care because of the small number of experimental years. Further measurements are needed to increase the validity of the results.

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