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A daily soil temperature model based on air temperature and precipitation for continental applications

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ABSTRACT: Soil temperature is a necessary component for estimating below-ground processes for continental and global carbon budgets; however, there are an insufficient number of climatic stations monitoring soil temperature. We used an 11-day running average of daily mean air temperature to estimate daily mean soil temperature at a depth of 10 cm using linear regression. This model was tested using data from 6 climate regions across the United States. Frequency analyses for 17 of 19 data sets showed that the number of days which were within a ±3.5 °C range centered on the measured soil temperature varied from 77 to 96%. The values of R^2 between observed and final predicted soil temperatures ranged from 0.85 to 0.96 with standard errors from 1.5 to 2.9 °C for all 19 simulations. Changes of soil temperature under snow cover were smaller than those without snow cover. Soil temperature under vegetation cover was also simulated assuming the rate of soil warming under vegetation cover would be reduced with increasing leaf area index according to the Beer-Lambert Law. Annual soil respiration can be estimated from the predicted soil temperature with reasonable accuracy. Daily soil temperature may be predicted from daily air temperature once regional equations have been established, because weather stations in the United States can be generalized into a few regions and sites within each region may use the same equation.

INTRODUCTION

Soil temperature is a critical variable controlling below-ground processes for global and continental carbon budgets. Whereas many stations across the United States have long-term records of daily air temperature and precipitation, few climate stations monitor soil temperature. Toy et al. (1978) used monthly mean air temperature to predict monthly soil temperature at continental scales. However, the influence of soil temperature on soil decomposition and respiration is exponential rather than linear (Edwards 1975, Raich & Schlesinger 1992), so simulations of belowground ecosystem processes for continental scales based on monthly time steps may be biased. Thus, a daily model of soil temperature is necessary.

Many analyses of soil temperature are based on the theories of heat flow and energy balance (Campbell 1977, Parton 1984, Stathers et al. 1985, Nobel & Geller 1987, Thunholm 1990). Theory-based models may provide accurate estimates of soil temperature at small scales, but may not be practical for estimation of soil temperature at continental and global scales. The many parameters required may depend on topography, soil texture, and soil water content – all of which may vary over short distances. Hasfurther & Burman (1974) used daily air temperature as a driving variable to predict daily soil temperature through a Fourier series analysis; but the model could be run only after convolution coefficients and correction factors were defined for a particular site. Models requiring coefficients that are defined for each particular site are also not practical for simulations over many different sites.

The objectives of this study are: (1) to develop a general methodology for estimation of daily soil temperature at continental scales using daily air temperature and precipitation data for bare ground; (2) to demonstrate how the predictions of soil temperature would effect annual soil respiration assuming different Q_{10} values; and (3) to simulate soil temperature under vegetation based on leaf area index (LAI). LAI can be remotely sensed from satellites (Tucker 1979, Asrar et al. 1984, Running et al. 1986, Peterson et al. 1987, Nemani & Running 1989). Thus, one may use remote sensing data with climate data to predict soil temperatures at continental scales.

BACKGROUND

Air temperature correlates well with soil temperature because both are determined by the energy balance at the ground surface. The daily amplitude of soil temperature at the surface is greater than the daily amplitude of air temperature for clear days and is less for cloudy days. A depth of 10 cm was selected for soil temperatures because most soil ecosystem processes occur within the top layers of soil (Buringh 1984, Pritchett & Fisher 1987). This model was developed first to estimate soil temperatures for bare ground because the soil temperature data obtained from weather stations are usually measured in places with little or no vegetation. Furthermore, vegetation can influence greatly the surface energy balance (Čermák et al. 1992), so it is necessary to adjust predicted bare-soil temperatures for different LAIs.

A time lag exists between air and soil temperatures due to the relatively large heat capacity of the ground. Nevertheless, typical lags between air temperature and soil temperature at a depth of 10 cm are approximately 4 h for minimum temperatures and 6 h for maximum temperatures (Lee 1978). As these time lags are less than 24 h, the same day's data may be used for model predictions of mean soil temperature. Soil temperature for a given day is usually considered to be the result of air temperatures in the past several days.

If snow is present, the relationship between air and soil temperatures will be different from that without snow due to insulation of the snow. Although the depth of snow cover on the ground may influence the rate of change in soil temperature, this influence is not considered in the model.

Between temperatures of 0 and 5 °C, root growth of most plants and germination of most seeds are inhibited (Soil Conservation Service 1975). Below-ground biochemical processes usually become inactive when soil temperature is below freezing. Therefore, whenever the predicted daily soil temperature is below 0 °C, it is assigned as 0 °C.

MODEL DESCRIPTION

Prediction of soil temperature under bare ground

The input data required are: (1) daily maximum air temperature (°C); (2) daily minimum air temperature (°C); and (3) daily precipitation (mm). Daily mean soil and air temperatures were calculated as the simple average of the daily maximum and minimum values. Daily maximum and minimum soil temperature data are available from the National Oceanic and Atmospheric Administration, Asheville, NC, USA. Daily maximum and minimum air temperature and precipitation data were obtained from EarthInfo, Inc. (Boulder, CO, USA; original source was the National Climatic Data Center). Selection of air temperature and precipitation data as driving variables is based on: (1) daily data are readily available; and (2) soil temperature may be more controlled by climate at large scales.

Eleven-day running averages of daily air temperature were processed on a yearly basis. An 11-day running average was selected after comparing preliminary results using 5-day to 31-day running averages. Running averages were determined in order to reduce the effects of extremes in air temperature. For the 11-day running averages, averaged air temperature on Julian Day 11 was the mean value of air temperatures from Julian Day 1 to Julian Day 11. Values of air temperature on the first 10 d were calculated using 1-day to 10-day running averages respectively. The 11-day running averages of air temperature were used as the independent variable and observed daily soil temperatures at 10 cm depth (without smoothing) as the dependent variable to establish linear regression equations for the 7 model development sites (Fig. 1).

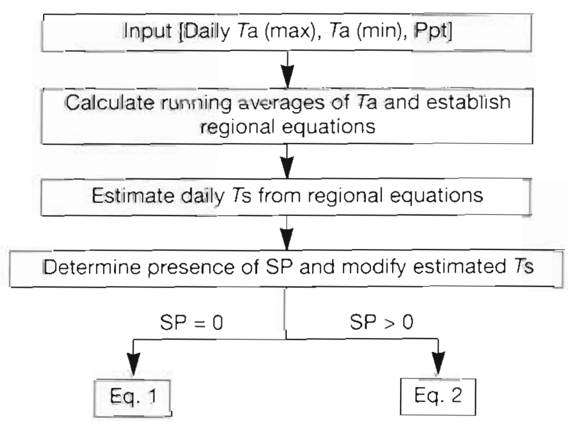


Fig. 1. Flow chart for predicting daily soil temperature from daily air temperature and precipitation data. *Ta*: daily mean air temperature in °C; *Ts*: daily mean soil temperature in °C; SP: amount of snowpack on the ground (water equivalent in mm); Ppt: precipitation in mm

The model calculates 1-dimensional snowpack (water equivalent in mm) on the ground according to the air temperature and precipitation data. The snowpack increases whenever the daily mean air temperature is below or equal to 0 °C and precipitation occurs on the same day; otherwise, there is no change in snowpack. The snowpack decreases or disappears whenever the mean air temperature is above 0 °C.

An initial value of snowpack (1-dimensional water equivalent in mm) and a snow-melt coefficient (mm d^{-1} $°C^{-1}$) are required as inputs. The depth of snowpack determines the day of the year when snow disappears. As the simulations begin on the first day of the year, the initial value for the depth of snowpack is based on data for the previous year, if available; otherwise, an estimated value is selected based on site information. The initial values for depth of snowpack in the model simulations varies from 0 to 30 mm. Snowmelt coefficients also vary from site to site and year to year because the 'quality' of snow can influence the melting rate. Therefore, estimated values for the snow melt coefficient are based on general site information, and varies from 0.3 to 1.2 mm d^{-1} $°C^{-1}$.

Estimated daily soil temperatures from the regional equations were modified according to determination of snowpack on the ground, because the rate of change in soil temperature under snow cover will be less due to snow's low thermal diffusivity and high albedo. When air temperature is above freezing, the snowpack will melt and the melt water will increase the heat capacity of the soil. Therefore, whenever a snowpack is present, soil temperature on the current day will not change much compared with the soil temperature on the previous day and Eq. (1) is used:

$$F(\mathrm{J}) = [A(\mathrm{J}) - A(\mathrm{J}-1)] \cdot M_1 + E(\mathrm{J}-1) \qquad (1)$$

where F(J) is the modified soil temperature on Day J starting on Julian Day 2, and the value of $F(1)$ is assumed to be $E(1)$; A(J) and A(J−1) are the observed daily air temperature on the current day and previous day respectively; E(J−1) is the soil temperature on the previous day solely estimated from the regional regression equation; and M_1 is a rate scaler of 0.1. When snowpack is not present, Eq. (2) is used:

$$F(\mathrm{J}) = [A(\mathrm{J}) - A(\mathrm{J}-1)] \cdot M_2 + E(\mathrm{J}) \qquad (2)$$

where E(J) is the soil temperature estimated from the regression equation on the current day; and M_2 is a rate scaler of 0.25. E(J) was used for Eq. (2) because the predicted temperatures have smaller errors than those using E(J−1).

The rate scalers M_1 and M_2, were selected initially from regressions of the running average of air temperature and the observed soil temperature for each site. Except for Alaska, the scalers were similar in magnitude, so in order to make the model simpler and more useful at large scales, constant values for M_1 and M_2 were used for all 7 model development sites. The annual means of the predicted soil temperatures using constant scalers were less than 0.6 °C different from those predicted from the regressions (except Alaska).

Prediction of soil temperature under vegetation

Experimental studies have shown that vegetation canopies can lower soil temperature during growing season significantly and reduce mean annual soil temperature (Li 1926, Jemison 1934, Qashu & Zinke 1964, Armson 1977, Munn et al. 1978, Čermák et al. 1992). Qashu & Zinke (1964) concluded that lower soil temperatures under oak or pine canopies may result from a lower rate of soil warming during spring time, whereas the rate of soil cooling is the same with or without canopy cover.

We hypothesize that a lower rate of soil warming under vegetation canopies results when less radiation is absorbed by the soil. According to the Beer-Lambert law, the fraction of radiation transmitted through a canopy is equal to $e^{(-K \cdot \mathrm{LAI})}$, where K is the extinction coefficient and LAI is the 1-sided leaf area index. Typical values of K are about 0.5 for different forest species (Jarvis & Leverenz 1984).

After estimation of daily soil temperature for bare ground, Eq. (3) is used for simulating soil temperatures under vegetation cover when $A(\mathrm{J}) > T(\mathrm{J}-1)$:

$$T(\mathrm{J}) = T(\mathrm{J}-1) + [A(\mathrm{J}) - T(\mathrm{J}-1)] \cdot M_2 \cdot \exp^{(-K \cdot \mathrm{LAI})} \qquad (3)$$

where T(J) and T(J−1) are the mean soil temperatures under vegetation on the current day and previous day respectively; and A(J) is the mean air temperature on the current day. When $A(\mathrm{J}) \leq T(\mathrm{J}-1)$, Eq. (4) is used:

$$T(\mathrm{J}) = T(\mathrm{J}-1) + [A(\mathrm{J}) - T(\mathrm{J}-1)] \cdot M_2. \qquad (4)$$

For evergreen conifers, the correction for LAI begins on Julian Day 2, and the soil temperature for the first day is determined as above.

METHODS

Selection of sites

Climatic regions can be defined using different principles for different scales from a single country to the whole globe. We used the Köppen climate classification (Strahler & Strahler 1989) modified with information from the National Climatic Data Center (NCDC) for the conterminous U.S. (Karl et al. 1988).

A total of 19 data sets of daily soil temperature at a 10 cm depth were selected for this study. Seven sites representing 6 different Köppen climatic regions in the USA were used to develop the model and establish the regional equations. The model was then tested both temporally using 7 data sets and spatially using 5 data sets. The years chosen for each site were selected on the basis of having the fewest number of days with missing data. Daily soil temperature for forested sites with known LAI could not be obtained.

Sites used for model development

The 7 selected sites are described in Table 1. They are: (1) Milton, Florida (FL84), representing a humid, warm-summer climate (Cfa); (2) Corvallis (Oregon State University), Oregon (OR84), a maritime, cool-summer site with little or no snow cover during the year (Cb); (3) Chatham Experimental Farm, Michigan (MI87), a humid-continental, cool-summer site with a long period of snow cover during the year (Dfb); (4) Jackson Experimental Station, Tennessee (TN84), a humid, warm-summer-site (Cfa); (5) Western Montana Branch Station, Montana (MT80), a cold and dry site (H); (6) Old Edgerton, Alaska (AK84), a subarctic site (Dfc); and (7) Safford, Arizona (AZ85), a subtropical desert site (BWh). Latitude ranges from 30.8 to 61.8° N among the 7 sites. Elevation ranges from 66 to 1096 m above sea level. Soils vary in texture from cobbly loam to clay loam; soil cover is either grass, sod or none. There is little variation in slope. Six of the 7 regional equations were generated using all 365 d of data for the given year; the regional equation for the site in Alaska, 1984, was generated using only the days when observed mean soil temperatures were ≥ 0 °C.

Data sets used for model testing

Twelve more data sets were used to test the model. Seven were from the same development sites but collected during different years to test the stability of the model over time (Table 2). Five different sites whose climatic types are similar to 5 of the 7 model development sites were used to test whether the model can be extended to large spatial scales (Table 3). The 5 sites are: (1) Gainesville, Florida (FL84p, paired with FL84); (2) New Mexico State University at Las Cruces, New Mexico (NM85p, paired with AZ85); (3) Geneva, New York (NY87p, paired with MI87); (4) Creston, Montana (MT80p, paired with MT80); (5) Raleigh-Durham, North Carolina (NC83p, paired with TN84). Data sets to pair with the model development sites in Oregon and Alaska were unavailable.

Table 1. Information for the 7 sites in different climatic regions across the United States. The data sets from these 7 sites were used for model development and establishing regional equations

Site: Location (U.S. state):	Cfa FL	H MT	Cb OR	Dfb MI	Cfa TN	BWh AZ	Dfc AK
Year	1984	1980	1984	1987	1984	1985	1984
Abbreviation	FL84	MT80	OR84	MI87	TN84	AZ85	AK84
Latitude (° N)	30.8	46.3	44.6	46.4	35.6	32.8	61.8
Longitude (° W)	87	114	123	87	89	110	145
Elevation (m)	66	1096	69	267	122	900	402
Soil type	Sandy loam	Cobbly loam	Clay loam	Sandy loam	Lintonia	Clay loam	Clay & sandy loam
Cover	Bare	Grass	Unknown	Sod	Grass	Bare	Sod
Slope (%)	2	2	2	3	0	0	0
Aspect (°)	90	180	250	180	–	–	–
Jan Ta[a]	8.0	-6.5	5.5	-6.6	-0.3	5.9	-15.7
Jul Ta	26.3	18.5	18.9	20.2	25.3	28.7	12.8
Ann. Ta	19.2	7.5	10.9	6.8	15.1	17.3	-1.5
Ann. Ts[b]	22.5	12.1	12.8	8.2	15.7	19.5	0.8
Ann. ΔT[c]	3.3	4.6	1.9	1.4	0.6	2.2	2.1
Ann. ppt[d]	1539	448	1234	828	1372	300	278
Missing data[e]							
Air	0	13	0	0	0	2	0
Soil	0	3	0	0	0	4	0

[a] Ta = mean air temperature (°C) for January, July, and for year
[b] Ts = mean soil temperature (°C) for January, July, and for year
[c] Difference of annual mean soil temperature and mean air temperature
[d] Annual precipitation (mm)
[e] No. of days during the year when data are missing

Table 2. Information for a second year of data for the 7 model development sites. These 7 data sets collected during different years were used for a temporal test of the model. See Table 1 for explanation of symbols

	FL	MT	OR	MI	TN	AZ	AK
Year	1987	1983	1988	1989	1987	1989	1989
Abbrev.	FL87	MT83	OR84	MI89	TN87	AZ89	AK89
Jan *Ta*	8.5	1.0	4.0	−4.5	3.0	6.5	−23.0
Jul *Ta*	27.0	17.0	19.5	20.5	26.5	28.5	16.0
Ann. *Ta*	18.5	7.5	11.5	5.5	16.0	18.0	−1.5
Ann. ppt	1844	311	953	620	1295	123	313
Missing data							
Air	0	0	0	0	0	0	2
Soil	0	0	0	0	0	0	0

Estimations of annual soil respiration

It has long been recognized that soil respiration rate increases exponentially with temperature; respiration increases about 2.4 times for a 10 °C increase in temperature (Q_{10} = 2.4) (Raich & Schlesinger 1992). We chose Q_{10} values of 2.0, 2.4, and 3.0 to examine how the range in measured Q_{10}'s affected the relative errors of annual soil respiration calculated from the predicted and measured soil temperatures.

Daily soil respiration is calculated as a specific rate times a function of daily soil temperature; daily soil respiration is then summed over a year to obtain the annual value. If the specific rate does not change over the year, then predicted relative annual soil respiration (Y_p, unitless) is calculated from the temperature function alone:

$$Y_p = \sum \exp\,[X \cdot F(\mathrm{J})] \quad (5)$$

where F(J) is the predicted soil temperature on Julian Day J (starting from Julian Day 1 to 365) and X is 0.07, 0.09, 0.11 for Q_{10}'s of 2.0, 2.4, or 3.0, respectively. Measured relative annual soil respiration (Y_m, unitless) is calculated by:

$$Y_m = \sum \exp\,[X \cdot G(\mathrm{J})] \quad (6)$$

where G(J) is daily measured soil temperature for each of the 7 model development sites. Errors in annual soil respiration were then determined by:

$$\%_{\mathrm{error}} = (Y_p - Y_m) / Y_m \cdot 100\,\%. \quad (7)$$

Statistical analyses

An aggregated equation including all 7 model-development sites was also produced and F tests [defined as MSE1/MSE2 where MSE is the mean square error or residual mean square, and the larger MSE is taken as numerator (Neter et al. 1990)] were used to determine whether there were significant differences between each of the 7 regional equations and the aggregated equation. A dummy variable was created for the aggregated equation and a t-test was used to determine whether there were significant differences among the 7 model-development sites. Frequency analysis was used to determine the accuracy of model prediction.

Table 3. Information for different sites which were paired with 5 of 7 model-development sites. The data sets from these 5 different sites were used for a spatial test of the model. See Table 1 for explanation of symbols

	FL	NM	NC	NY	MT
Year	1984	1985	1983	1987	1980
Abbrev.	FL84p	NM85p	NC83p	NY87p	MT80p
Paired site	FL	AZ	TN	MI	MT
Lat. (°N)	29.6	32.3	35.9	42.9	48.2
Long. (°W)	82	107	79	77	114
Elev. (m)	29	1183	115	219	896
Soil type	Sandy loam	Belen clay	Silty loam	Silt loam	Silt loam
Cover	Bare	Bare	Sod	Sod	Bare
Slope (%)	6	0	5	0–3	2
Aspect (°)	315	–	225	90	180
Jan *Ta*	12.0	4.0	3.5	−3.5	−8.5
Jul *Ta*	26.5	26.5	26.5	22.0	17.5
Ann. *Ta*	21.5	16.5	15.0	9.0	6.5
Ann. ppt	997	319	1200	862	627
Missing data					
Air	0	0	0	0	0
Soil	0	0	0	0	0

RESULTS AND DISCUSSION

There were strong relationships between the averaged daily air temperatures and observed daily soil temperatures at the 10 cm depth for all 7 model development sites; R^2 values ranged from 0.86 to 0.97 (Fig. 2). With the exception of Oregon (due to its maritime climate), the absolute value of the regression intercepts increased with the increase in latitude, perhaps because the sites located in higher latitude usually have greater variability of air and soil temperatures. At a similar latitude, a moist site (MI) has a smaller variation than that of a dry site (MT).

These 7 linear regressions were considered as regional equations. The relationship between observed and estimated soil temperatures will be exact if the intercept (b_0) = 0 and the slope (b_1) = 1; b_0 and b_1 for 6 of the 7 development sites were not significantly different from 0 and 1, respectively (data not shown). The poor correlation for the Alaska site resulted from: (1) the data used for establishing the equation are from days with observed soil temperatures ≥0 °C only; and (2) the assignment of predicted soil temperatures below freezing as 0 °C. Predicted soil temperatures for 6 of the 7 development sites (FL, OR, TN, AZ, MT, MI) show close correspondence with observed soil temperatures (Fig. 3).

Predicted soil temperatures from the regional equations and observed soil temperatures were strongly correlated in all 19 simulations (Table 4). While the number of days with estimated errors within ±2.0 °C ranged from 46 to 82, averaging 60 % (data not shown); the number of days with errors within ±3.5 °C ranged from 64 to 96, averaging 84 % of the year. Values of R^2 ranged from 0.85 to 0.96 and the standard error of estimates ranged from 1.5 to 2.9°C. The model responds to changes of both temporal and spatial dimensions with reasonable accuracy (Table 4).

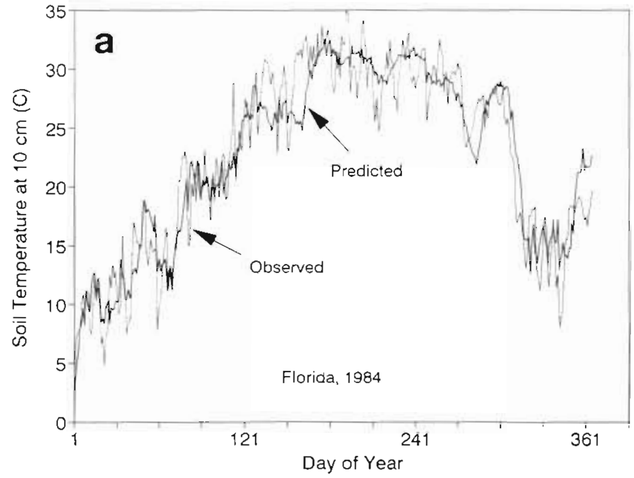


Fig. 3. Comparisons of predicted daily soil temperatures with observed values at 10 cm depth for the 7 model development sites: (a) FL84, (b) OR84, (c) AK84, (d) TN84, (e) AZ85, (f) MT80, and (g) MI87

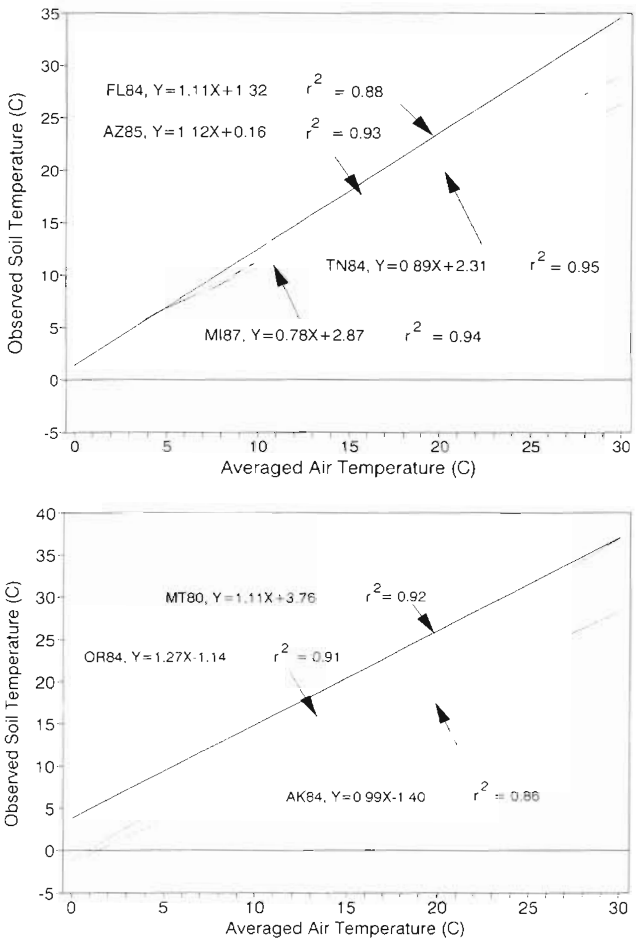
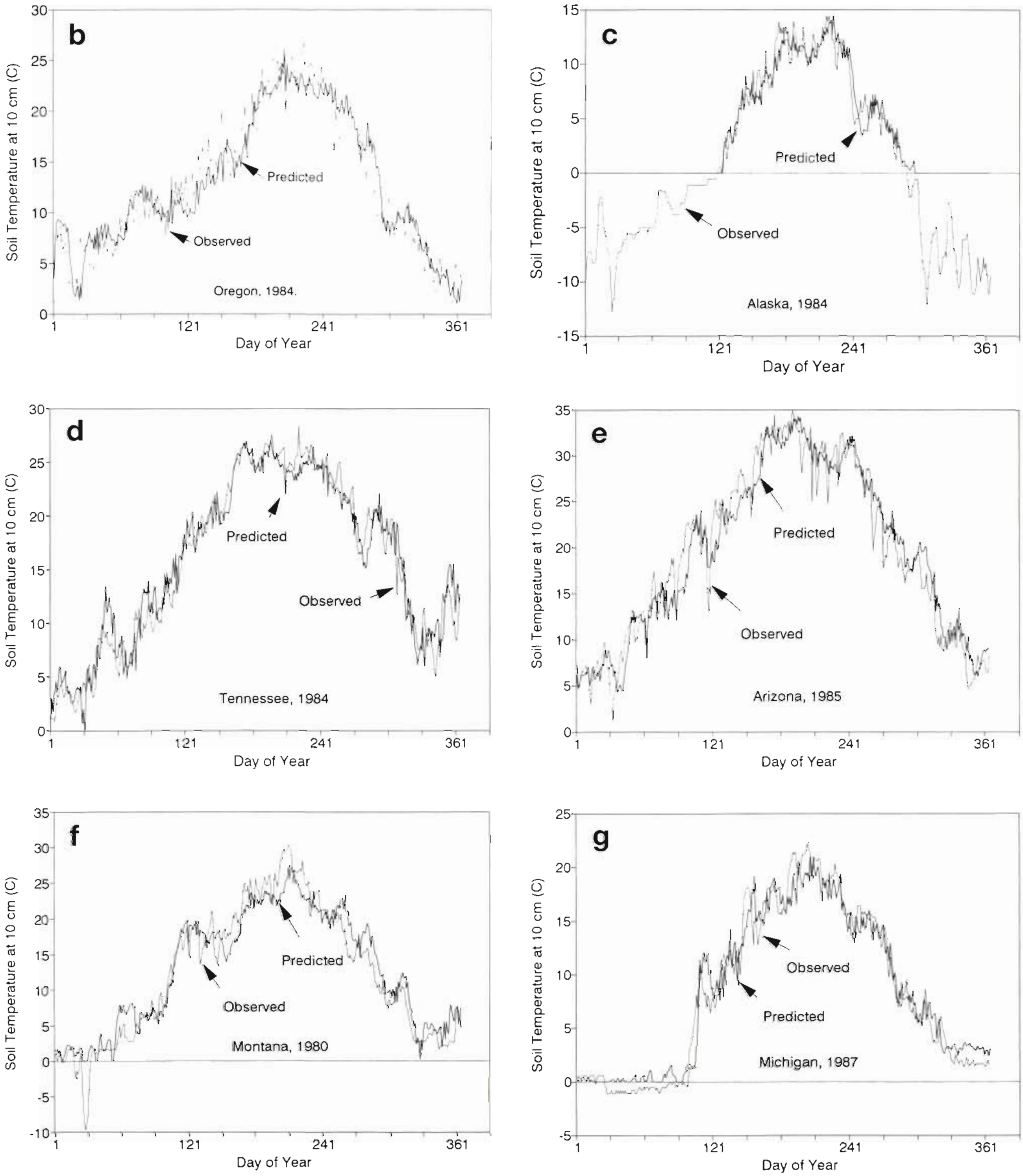


Fig. 2. Relationships between air temperatures (°C) after 11-day running averages and soil temperatures (°C) at 10 cm depth for the 7 model-development sites representing different climatic regions in the U.S. The equation for the site in Alaska was generated using only the days when observed mean soil temperatures are ≥0 °C (N = 169); the others were from 365-day data for the given years

Although significant errors existed between the predicted and observed soil temperatures for the Alaska site (Fig. 3c, Table 4), the result was better than that achieved by not assigning 0 °C to the days when the predicted soil temperature was <0 °C, because the regression equation was generated from the days with observed soil temperatures ≥0 °C. Using all 365 d of data for the regression equation improved winter-time predictions of soil temperature, but underestimated actual soil temperatures during growing season. Also, a significant improvement in prediction of soil temperature could be achieved for the Alaska site if the constant rate scalers (M_1 and M_2) were tuned for this site. For soil biological processes, it is more important to have a better soil temperature estimation during the growing season than to have better estimation during the winter time for sites like Alaska.

The predictions of soil temperature from some of the data sets used for model testing are better than the predictions from the data used for model development. Although regional equations should be tested for each new area, these results suggest that most sites within the same climatic region could use the same equation. However, both *F*- and *t*-tests showed there were significant differences between each of the 7 regional equations and an aggregated equation as well as the differences among the 7 regional equations at the 0.05 level. Substantial differences exist between the results from the regional equations and the aggregated equation for the 7 model-development sites (Table 5). Thus, it may not be appropriate to use a single regression equation to predict daily soil temperature from daily air temperature over a continent.



For all 7 model-development sites, the average annual soil temperature at a 10 cm depth is higher than the average annual air temperature (Table 1). Higher average soil temperatures have been reported before (Shulgin 1978, Toy et al 1978) and might be expected in light of the low specific heat of soil and the reduced air mixing that usually occurs in the air layer adjacent to the soil surface (Toy et al. 1978). The variations range from 0.6 at TN to 4.6 °C at MT; these differences are probably caused by climate. For example, larger difference be-

Table 4. Frequency analyses of predicted soil temperatures for all 19 simulations including 7 for model development sites and 12 data sets for model testing

Abbrev.	% of days with error of: ≤3.5 °C	>5 °C	R^2 [a]	SE [b]
FL84*	81	5	0.89	2.6
FL87†	83	6	0.88	2.7
FL84p	84	6	0.88	2.4
OR84*	91	1	0.91	2.0
OR88†	93	2	0.93	1.9
MI87*	96	0	0.96	1.5
MI89†	78	9	0.93	2.2
NY87p	90	2	0.95	1.8
TN84*	95	1	0.95	1.8
TN87†	95	1	0.95	1.7
NC83p	77	4	0.95	2.1
AZ85*	87	2	0.94	2.3
AZ89†	82	7	0.94	2.3
NM85p	91	0	0.95	2.2
AK84*	64	28	0.85	2.9
AK89†	70	18	0.92	2.2
MT80*	85	4	0.94	2.3
MT83†	82	3	0.94	2.2
MT80p	80	7	0.95	1.9

[a] Coefficient of determination from linear regression between observed and predicted soil temperatures
[b] Standard error for predicted soil temperature
*Data sets used for model development
†Data sets used for model testing on temporal dimension; data sets denoted by p were used for model testing on spatial dimension

Table 5. Comparison of soil temperature predictions from regional equations (R) and aggregated equation (A) for all 7 model development sites

Site abbrev.	% of days with error of: ≤3.5 °C		>5 °C	
	R	A	R	A
FL84	81	69	5	13
OR84	91	80	1	3
MI87	96	88	0	3
TN84	95	87	1	2
AZ85	87	78	2	3
AK84	64	35	28	38
MT80	85	68	4	20

Table 6. Percent errors of annual soil respiration calculated from the predicted daily soil temperatures and measured soil temperatures (Eq. 7) with various Q_{10} values at the 7 model development sites

Site abbrev.	Q_{10} = 2.0	Q_{10} = 2.4	Q_{10} = 3.0
FL84	-2	-2	-4
OR84	-1	-2	-3
MI87	-1	-2	-4
TN84	-1	-1	-2
AZ85	-1	-2	-3
AK84 [a]	-1	-1	-2
MT80	-1	-3	-6

[a] During the period that observed soil temperatures ≥0 °C

tween air and soil temperatures at MT may result from both a longer time period of snow cover during winter and less precipitation during summer. Explanation for this can be developed from the use of detailed, physical models of soil temperature.

Relative annual soil respirations estimated from the predicted soil temperatures were slightly less than those determined using measured soil data (Table 6). As expected, the relative errors increase with an increase in the Q_{10} value. For any given day, large errors in predicted soil temperature would cause substantial errors in the predicted soil respiration, but the errors in predicted soil temperature were not strongly biased so the annual estimates of soil respiration had small but consistent relative errors.

Soil temperatures for deciduous and coniferous forests at the Tennessee site, 1984, were simulated using LAI of 5 (Fig. 4). The period of simulation for the deciduous forest was from Julian Day 97 to 307 (Hutchison & Baldocchi 1989). After leaf emergence, the warming rate of soil temperature was substantially slowed down; after leaves senesced, the soil eventually reached the same temperature as that of bare ground. For coniferous forest, the influence of vegetation on soil temperature lasted the entire year. Soil temperature under forest cover in the northern hardwood ecosystem increases gradually compared with that at bare ground and reaches the maximum in August (Armson 1977) which agrees well with the trends in Fig. 4.

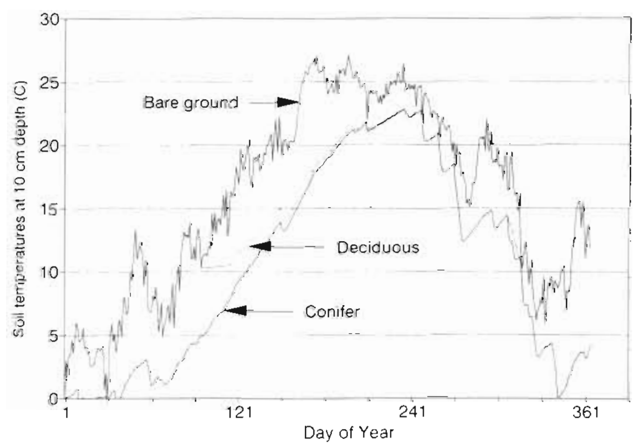


Fig. 4. Simulation of soil temperatures for conifer and deciduous forests using the Tennessee, 1984, climate data. The simulation results are compared to the predicted soil temperatures for bare ground (Fig. 3d)

CONCLUSIONS

Daily soil temperature at 10 cm depth for various sites and years may be predicted from daily air temperature, once equations have been established for different climatic regions. For site-specific applications, the accuracy of the predictions can be improved by determining if snowpack is present. The predicted soil temperatures are reasonably accurate for simulating biological processes, such as soil respiration, on an annual time step. We suggest that this methodology may be appropriate for predicting daily soil temperature from daily air temperature at large scales, because thousands of weather stations can be generalized into a few regions and the sites within a region may use the same equation. It may be possible to estimate soil temperature under vegetation cover at regional and continental scales using LAI estimated from satellites.

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