Research article

Predicting Soil Temperature Condition in Agricultural Land under Climate Change in Japan

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Abstract Decomposition of soil organic carbon as well as growth of crops are affected by soil physical condition such as soil moisture and soil temperature. Thus predicting soil moisture and temperature condition of arable lands under future climate change is important for both mitigation and adaptation of climate change in agriculture. In this study, we attempted to predict soil temperature condition in arbitrary arable lands in Japan. Soybean fields of Toyama city, middle part of Japan facing Japan Sea were chosen as the experimental site. There, monitoring of soil temperature and measurement of soil thermal properties which is a function of soil moisture, was conducted. For the future application to arbitrary locations, the thermal properties were also predicted with a mathematical model, by using soil physical properties such as the ratio of sand: silt :clay, soil particle density and dry bulk density in soil physical database. Then, numerical simulation of soil moisture and temperature was conducted with predicted soil hydraulic and thermal properties. The model with estimated thermal properties described the measured soil temperature fairly well especially when the soil condition was wet.

Keywords climate change, thermal conductivity, soil temperature, soil database, numerical simulation

INTRODUCTION

Soil is a foundation of agriculture and ecosystem. Growth of crops and vegetables, and/or incidence of insect and pest as well as decomposition of soil organic matter are affected by soil physical condition such as soil moisture and soil temperature (e.g. Allmaras et al., 1964; Singh and Dhaliwal, 1972; Simunek and Suarez, 1993). Climate change including temperature rise and change in rainfall patterns will alter soil physical conditions. For example, Bai et al. (2014) showed that soil temperature at depth of 50 cm has increased at an average rate of 0.79 ℃ per decade from 1982 to 2000 in Mojav Desert region in USA and mentioned that the temporal changes of soil temperature was correlated with those of air temperature. The available observed data of soil temperature and soil moisture has been limited spatially and temporarily compared to the meteorological data.

Numerical simulation of soil water and heat movement with GCM (General Circulation Model) projections as boundary condition is one of the effective way to predict future soil physical condition. Kato and Nishimura (2015) proposed the methods of temporal downscaling of GCM prediction, especially the rainfall data, for producing boundary conditions for numerical simulations of soil moisture, and applied the downscaled projections to prediction of future soil moisture of an agricultural land in Japan. Kato and Nishimura (2016) attempted to estimate soil hydraulic parameters for numerical simulation of soil moisture in arbitrary agricultural lands by using soil physical properties database Solphy J (Eguchi et al., 2011). As for the soil temperature, Kato et al. (2011), for example, conducted the numerical simulation of soil temperature of agricultural field to reproduce the past temperature records with measured soil thermal conductivity. For the further application, it is beneficial to predict soil temperature in arbitrary locations without measurement of soil thermal properties. Since soil thermal properties are generally affected by soil physical properties such as soil texture, soil bulk density, etc., soil physical properties databases are probably useful for estimation of soil thermal properties and subsequent simulation of soil temperature.

Based on the above, in this study, we investigated the possibility of estimation of soil thermal properties by using available soil physical properties databases and prediction of soil temperature under climate change in arbitrary agricultural lands.

METHODOLOGY

Study Site

One of the plain agricultural field in Toyama city, the middle part of Japan facing Japan Sea, was chosen as the study site (Fig. 1). Hokuriku District, including Toyama city is the representative grain growing area in Japan and has often been chosen as research sites for effects of climate change on agriculture (MEXT, 2015). Recently, a multiple cropping system of paddy rice-barley-soybean in two years has often been employing in the region around our study site. Barley and soy beans were grown from November 2010 to May 2011, and from June to October 2011, respectively, at Agricultural Research Institute of Toyama Prefectural Agricultural, Forestry and Fisheries Research Center in Toyama City. There, soil moisture and temperature at depths of 5, 10, 20, 30 and 40cm was monitored continuously with ECH2O 5TE sensors (Decagon Devices, Inc., USA) from April to October, 2011. Undisturbed 100 cm^3 core samples and disturbed soil were sampled from a pit in the field and then soil samples were brought back and their physical properties (soil texture, particle density, water retention, saturated hydraulic conductivity) were measured in the laboratory (Kato and Nishimura, 2016). Soil thermal conductivity λ_{meas} was also measured with KD2 heat probe (Decagon Devices Inc. USA).

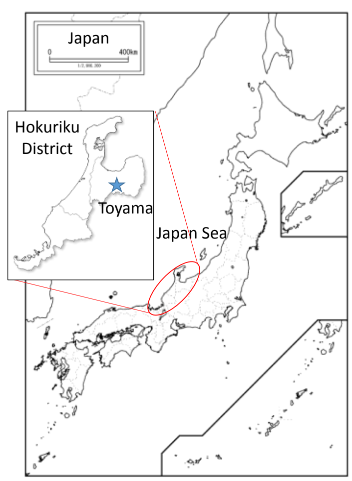

Fig. 1 The location of Toyama City (Kato and Nishimura, 2016, modified)

Numerical Model

HYDRUS-1D model has widely been used for calculation of soil moisture and temperature, and in this study, the ver. 4.xx (Šimůnek et al., 2013) was used. Since heat is also transported with water, and soil thermal properties often changes with soil moisture condition, both soil moisture and soil temperature were simulated simultaneously. The governing equation of liquid and vapor water movement in soils was an extended Richrads' equation with root water uptake *S*(*h*) (Eq. (1)).

$$\frac{\partial \theta_T(h)}{\partial t} = \frac{\partial}{\partial x}\left[(K + K_{vh})(\frac{\partial h}{\partial x} + 1) + (K_{LT} + K_{vT})\frac{\partial T}{\partial x} \right] - S(h) \tag{1}$$

where *h* is the pressure head [L], θ_T is the total volumetric water content, or the sum of the volumetric water content of liquid (θ) and vapor (θv) water [L^3L^{-3}], respectively. *T* is temperature [K], *K* and K_{LT} are the isothermal and thermal hydraulic conductivity of the liquid phase [LT^{-1}], K_{vh} and K_{vT} are the isothermal and thermal vapor hydraulic conductivity, respectively[LT^{-1}].

Heat transfer with vapor transport was described with heat flow equation (Eq. (2)).

$$C_p(\theta)\frac{\partial T}{\partial t} + L_0\frac{\partial \theta_v}{\partial t} = \frac{\partial}{\partial x}\left[\lambda(\theta)\frac{\partial T}{\partial x} \right] - C_w\frac{\partial T}{\partial x} - C_v\frac{\partial q_v T}{\partial x} - L_0\frac{\partial q_v}{\partial x} \tag{2}$$

where *C* is the volumetric heat capacity and subscript *p*, *w*, and *v* mean porous medium, liquid water and vapor, respectively, L_0 is the volumetric latent heat of vaporization of liquid water [$ML^{-1}T^{-2}$] and q_v is the vapor flux density [LT^{-1}]. λ is the apparent thermal conductivity of the soil [$M\,LT^{-3}K^{-1}$] which is the sum of the thermal conductivity of the porous medium under no flow condition λ_0 (θ) and the macrodispersivity. The details can be found in Šimůnek et al. (2013).

Soil Hydraulic Parameters

In this study, van Genuchten-Mualem (VG-M) model (van Genuchten, 1980) Eq. (3) and (4) was employed for predicting water retention curves and unsaturated hydraulic conductivity.

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} = \left(1 + |\alpha h|^n\right)^{-m} \tag{3}$$

$$K(h) = K_s S_e^l \left[1 - (1 - S_e^{1/m})^m\right]^2 \tag{4}$$

where θ_r and θ_s are the residual and saturated volumetric water content [L^3L^{-3}], K_s is the saturated hydraulic conductivity [LT^{-1}], S_e is the effective saturation [dimensionless], α [L^{-1}], *l*, *m*=1-1/*n*, and *n* [dimensionless] are empirical parameters.

Hydraulic parameters of VG-M model for soils of each layer were determined based on the digital soil map (Takata et al., 2009) and the agricultural soil-profile physical properties database, Japan "SolphyJ" (Eguchi et al., 2011). Here, calculation area was divided into three layers according to SolphyJ database and dataset of water retention, i.e., volumetric water contents at suctions of 32, 500, 16000 and 320000 cmH_2O of each soil layer were prepared. Then "RETC program" (Yates et al., 1992), which can predict parameters of soil hydraulic functions such as VG-M model by fitting observed water retention by nonlinear least-squares method, was used for determining the VG-M parameters. The saturated hydraulic conductivity "K_s" value was predicted with a neural network based model "Rosetta" (Schaap et al., 1998). The recommended value 0.5 was employed as *l*. The details can be found in Kato and Nishimura (2016).

Soil Thermal Parameters

Volumetric heat capacity *C* (θ) and thermal conductivity λ_0 (θ) vary among soils. Considering the application to arbitrary locations, both *C* and λ_0 were determined with the soil properties database.

Volumetric heat capacity of soil can be described as the sum of heat capacities of the constituents as follows (Šimůnek et al., 2013),

$$C_{soil} = C_n\theta_n + C_o\theta_o + C_w\theta + C_a a_v \approx (1.92\theta_n + 2.51\theta_o + 4.18\theta)10^6 \quad \text{(J m}^{-3}\text{K}^{-1}\text{)} \tag{5}$$

where C means heat capacity and subscription of n, o, w and a are solid, organic matter, water and air, respectively and a_v is the volumetric fraction of air. θ_n can be found in SolphyJ database and θ_o can also be obtained assuming that particle density of organic matter is 1.63 (g cm^{-3}).

Models have been proposed to estimate soil thermal conductivity. In this study, Chung and Horton (1980) (C-H) model and Campbell (1985) model were employed.

Chung and Horton (1980) described soil thermal conductivity as follows (Eq.(6)).

$$\lambda_{CH} = b_1 + b_2\theta + b_3\theta^{1/2} \tag{6}$$

where b_1, b_2 and b_3 are empirical parameters. Chung and Horton (1980) proposed the sample set of b_1~b_3 corresponding with "sand", "loam", and "clay" and hereafter we call those λ_{CH} as λ_{sand}, λ_{loam} and λ_{clay}, respectively.

According to Campbell (1985), soil thermal conductivity is describes as follows (Eq. (7)).

$$\begin{aligned}
&\lambda_{camp} = A + B\theta - (A - D)\exp\{-(C\theta)^E\} \\
&A = \frac{0.57 + 1.73\theta_q + 0.93\theta_m}{1 - 0.74\theta_q - 0.49\theta_m} - 2.8\theta_n(1-\theta_n), \quad B = 2.8\theta_n \\
&C = 1 + 2.6\theta_c^{-1/2}, \quad D = 0.03 + 0.7\theta_n^{\,2}, \quad E = 4
\end{aligned} \tag{7}$$

where subscription q, m and c represent quartz, minerals other than quartz, and clay, respectively, and ρ_d and ρ_s are soil dry bulk density and soil particle density, respectively. θ_q, θ_m, and θ_c can be calculated as equations (8) assuming that the entire sand fraction is originated from quartz, while silt and clay are from other minerals

$$\theta_n = \rho_d/\rho\,, \ \theta_q = \theta_n \times \theta_{Sand}\,(\%)\,, \ \theta_m = \theta_n - \theta_q\,, \ \theta_c = \theta_n \times \theta_{Clay}\ (\%) \tag{8}$$

where θ_{sand} and θ_{clay} are the volumetric fraction of sand and clay, respectively. Here, mass ratio of sand and clay in SolphyJ database were substitute for θ_{sand} and θ_{clay}, respectively. Though both ρ_d and ρ_s can be found in Solphy J database, here, three different ρ_d (ρ_{d1}, ρ_{d2}, and ρ_{d3}) were employed for Eq. (8) as follows since soil bulk density easily changes with cultivation.

$$\rho_{d2} = \rho_{d1} - 0.10, \ \rho_{d3} = \rho_{d2} - 0.10 \tag{9}$$

where dry bulk density value in Solphy J database were employed for ρ_{d1}. In this study, ρ_{d1}=1.02, ρ_{d2}=0.92, and ρ_{d3}= 0.82 were used for the simulation. Hereafter we call λ_{camp} which were predicted with ρ_{d1}, ρ_{d2}, ρ_{d3} as $\lambda_{1.02}$, $\lambda_{0.92}$, $\lambda_{0.82}$, respectively.

Scenario Study

Using determined parameters, scenario study was conducted to predict soil moisture and temperature of arable lands in Toyama under climate change. ELPIS-JP (Iizumi et al., 2012) is approximately 20 km scale daily GCM projection dataset of "50 time series" of 110 years. The "50 time series" represents variability of meteorological phenomena incident to temporal downscaling of GCM projections (Iizumi et al., 2012). Corresponding to Toyama weather station, MIROC 3.2 hires and A1B of Toyama weather station data were employed for GCM and IPCC SRES Scenario, respectively. Since temporal scale of soil water and heat movement in agricultural lands are usually shorter than a day, daily ELPIS-JP dataset was temporally downscaled into hourly or shorter scale by using weather generator CLIGEN (Nick et al., 1995). Details of temporal downscaling methods can be found in Kato and Nishimura (2015). According to the climate scenario of the possible monthly rainfall depth of the soybean growing period (June, July, August and September), expected maximum values in present (1981-2000) are 291, 405, 346 and 363 mm, respectively, and those values in future (2071 to 2090) tend to increase to 1.3 ~ 1.6 times of those of present, except August. Average monthly air temperature of four months from June in present are projected to be 24.4, 28.6, 30.4 and 25.9 ℃, respectively and are likely to rise 3~5 ℃ through a year in late 21st century. Here, we attempted to predict soil moisture and temperature with an assumption of maximum monthly rainfall in June both in "present" and "future" (Kato and Nishimura, 2015).

RESULTS AND DISCUSSION

Determined hydraulic parameters are shown in Table 1 and Kato and Nishimura (2016) reported that the model described soil moisture well with RMSE (root mean square error) of 0.01 $cm^3\ cm^{-3}$.

Table 1 Determined soil hydraulic parameters of each layer

Location	Level	θ_r ($cm^3\ cm^{-3}$)	θ_s ($cm^3\ cm^{-3}$)	α	n	K_s (10^1 cm d^{-1})	l
Toyama	1	0.027	0.470	0.043	1.11	18.9	0.5
	2	0.029	0.361	0.032	1.11	11.6	0.5
	3	0.009	0.468	0.046	1.12	72.0	0.5

Soil thermal diffusivity K_a, which is calculated by the ratio of thermal conductivity λ_a to volumetric heat capacity C_a, is an indicator of the ability of soil to have temperature change with heat inflow. Hereafter we call the thermal diffusivities calculated with λ_{sand}, λ_{loam}, λ_{clay}, $\lambda_{1.02}$, $\lambda_{0.92}$, and $\lambda_{0.82}$ as K_{sand}, K_{loam}, K_{clay}, $K_{1.02}$, $K_{0.92}$, and $K_{0.82}$, respectively. Figure 2 shows the comparison of soil thermal diffusivities among those determined with (a) C-H model (K_{sand}, K_{loam} and K_{clay}) and (b) Campbell model ($K_{1.02}$, $K_{0.92}$, and $K_{0.82}$). Both figures also show K_{meas}, which were calculated with measured soil thermal conductivity λ_{meas} fitted with C-H model. Compared with the measured values, C-H model overestimated thermal conductivities and thus thermal diffusivities (Fig. 2 (a)). Especially, K_{sand} is four times larger than $K_{meas.}$ This discrepancy is probably due to the difference in soil bulk density and type of minerals which constitute the soil. Campbell model, which can partly consider some of physical properties, tended to describe the thermal diffusivities better than C-H model and the predicted values were improved by assuming the lower dry bulk density, especially when soil moisture is high (Jury and Horton, 2004) (Fig. 2(b)).

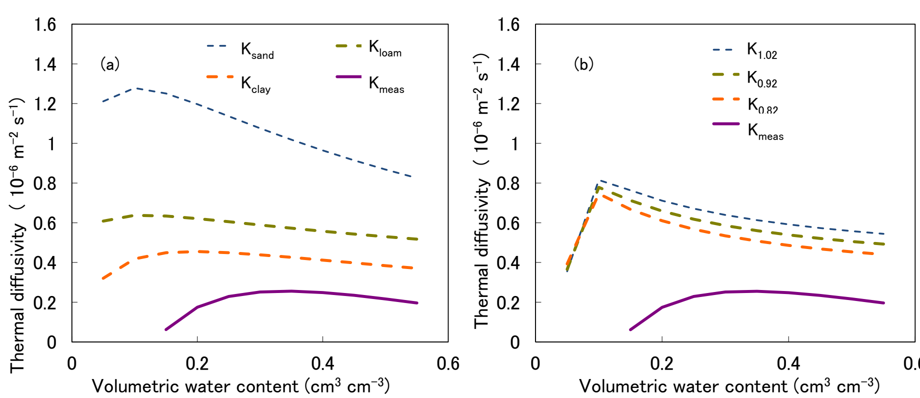

Fig. 2 Estimated thermal diffusivities with (a) Chung and Horton and (b) Campbell models

Figure 3 shows the comparison of measured and simulated soil temperature at depth of 10cm in the study field. Simulated values were calculated by using measured thermal conductivity λ_{meas}. The model described the measured soil temperature well with RMSE = 1.7 ℃.

Figure 4 shows the comparison of the simulated vertical distribution of soil temperature among those calculated with five different thermal conductivity, or λ_{sand}, $\lambda_{1.02}$, $\lambda_{0.92}$, $\lambda_{0.82}$ and λ_{meas} on a (a) dry day (the sunny day after a few sunny days in succession) and (b) wet day (the day after a rainy day), and Fig.4(c) shows the simulated vertical distribution of volumetric water content of the dry day (a) and the wet day (b) of Fig. 4. Simulated soil temperature with λ_{sand} was larger than other simulated results regardless of the soil moisture condition. On the other hand, simulated results with Campbell model ($\lambda_{1.02}$, $\lambda_{0.92}$, and $\lambda_{0.82}$) agreed well with that with λ_{meas} under wet soil condition. It might be reflected that the thermal diffusivities $K_{1.02}$, $K_{0.92}$, and $K_{0.82}$ at high water content are more similar to K_{meas} than those at low water content (Fig. 2). Campbell model gives smaller thermal diffusivity at low water content due to the exponential function with water content as a variable (Eq.7). Probably this made it quite difficult to evaluate thermal conductivity of soil under dry condition. Changes in dry bulk density in the estimation of soil thermal conductivity did not affect predicted soil temperature so much (<1 ℃) compared to changes in soil moisture condition (Jury and Horton, 2004).Those results indicated that in wetted seasons or humid regions such as Japan, soil temperature can be predicted with acceptable preciseness by using soil thermal conductivity which estimated with Campbell model by using SolphyJ database.

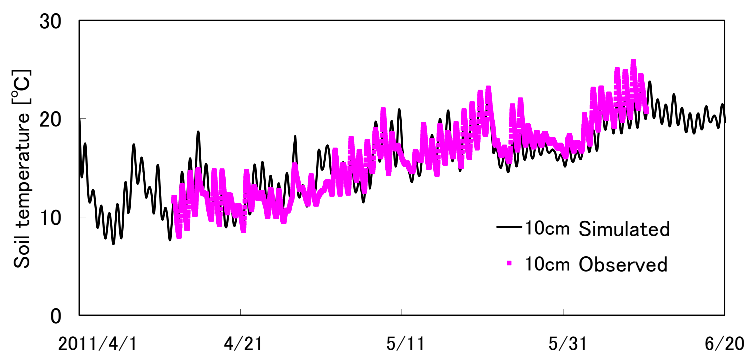

Fig. 3 Comparison of the simulated and observed soil temperature at depth of 10 cm

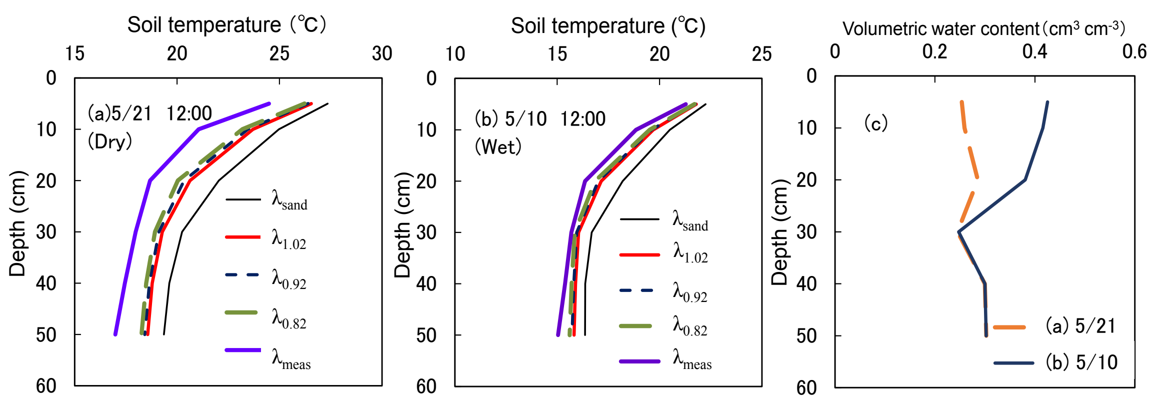

Fig. 4 Comparison of the simulated vertical distribution of the soil temperature predicted with estimated thermal conductivities on a dry day (a) and a wet day (b), and the simulated vertical distribution of soil moisture of both days (c)

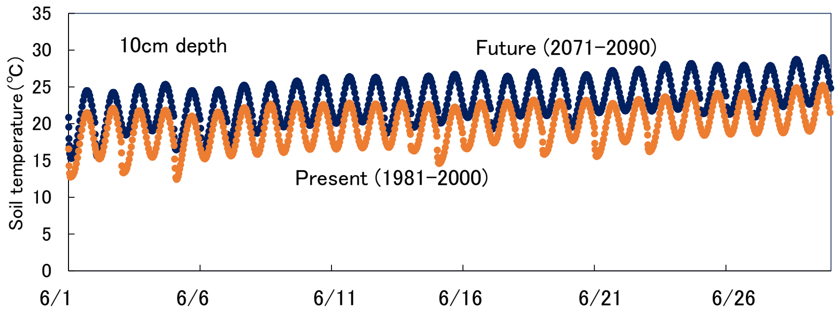

Fig. 5 Comparison of the simulated and observed soil temperature at depth of 10cm between "future" and "present"

Figure 5 shows the comparison of simulated soil temperature at depth of 10cm between "present" and "future". $\lambda_{1.02}$ was employed in this scenario study. In the future, soil temperature may rise three to five degrees accompanies with rising air temperature. In this way, the quantitative discussion about soil temperature in the future in arbitrary agricultural lands maybe possible with estimated thermal conductivity.

CONCLUSION

In this study, we investigated the proper method of estimating soil thermal properties by using digital soil map and the soil physical database in order to predict soil temperature in arbitrary agricultural lands. Soil thermal conductivity could be estimated with mathematical model by using soil physical properties such as the ratio of sand: silt :clay, soil particle density and dry bulk density in the soil physical database. Soil temperature was well described the past soil temperature records with numerical simulation by using estimated parameters especially when the soil is wet. This result indicated that it may be possible to predict soil moisture and soil temperature quantatively with the combination of soil physical properties database and downscaled climate model projections especially for the high humid regions such as Asian countries.

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