Evaluation of 14 frozen soil thermal conductivity models with observations and SHAW model simulations

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Abstract
Frozen soil thermal conductivity (FSTC, $\lambda_{eff}$) is a critical thermophysical property that is required for a variety of science and engineering applications. Measurements of $\lambda_{eff}$ in frozen soils are prone to errors because the currently available thermal methods result in phase change (i.e., thawing and refreezing of ice) that affects the estimated $\lambda_{eff}$, especially near the freezing point of soil water (e.g., −4 to 0 °C) where rapid phase change occurs. In addition, measured $\lambda_{eff}$ data are few compared to other physical properties. Therefore, many FSTC algorithms have been developed and a few of them have been incorporated in numerical simulation programs for calculating $\lambda_{eff}$. However, large discrepancies between simulated and observed soil thermal regimes have been reported. Previous studies either evaluated the performance of a few FSTC algorithms with limited $\lambda_{eff}$ or simply compared the performance of the algorithms in numerical simulation programs. No study has been performed to systematically assess the performance of the FSTC algorithms included in numerical simulation programs with both observations and model simulations. In this study, 14 FSTC algorithms incorporated in various numerical simulation programs were evaluated with a compiled dataset consisting of 331 $\lambda_{eff}$ measurements on 27 soils from seven studies made at temperatures on or below −4 °C. The Becker 1992 algorithm provided the best estimates of the $\lambda_{eff}$ measurements, but the accuracy of the estimates was not good (i.e., RMSE = 0.46 W m$^{-1}$ °C$^{-1}$, Bias = -0.04 W m$^{-1}$ °C$^{-1}$ and NSE = 0.51). These FSTC algorithms were also incorporated in the Simultaneous Heat and Water (SHAW) model to compare their effects on the simulating soil temperature and water content at two field sites with contrasting soil textures in USA. The simulation results showed that the average bias of simulated and observed soil temperature for all depths ranged from −2.2 to 2.8 °C and the average differences of liquid water content ranged from −0.08 to 0.1 cm$^3$ cm$^{-3}$. Generally no FSTC algorithm combined with the SHAW model satisfactorily estimated the dynamic soil thermal regime. Perspectives on future studies are discussed.

Keywords
Frozen soil thermal conductivity algorithms, SHAW model, Performance evaluation, Liquid water content, Ice content

Disciplines
Agriculture | Soil Science | Theory and Algorithms

Comments
This article is published as He, Hailong, Gerald N. Flerchinger, Yuki Kojima, Dong He, Stuart P. Hardegree, Miles F. Dyck, Robert Horton et al. "Evaluation of 14 frozen soil thermal conductivity models with observations and SHAW model simulations." Geoderma 403 (2021): 115207. doi:10.1016/j.geoderma.2021.115207.

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ARTICLE INFO
Handling Editor: Cristine L.S. Morgan

Keywords:
Frozen soil thermal conductivity algorithms
SHAW model
Performance evaluation
Liquid water content
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ABSTRACT

Frozen soil thermal conductivity (FSTC, $\lambda_{eff}$) is a critical thermophysical property that is required for a variety of science and engineering applications. Measurements of $\lambda_{eff}$ in frozen soils are prone to errors because the currently available thermal methods result in phase change (i.e., thawing and refreezing of ice) that affects the estimated $\lambda_{eff}$, especially near the freezing point of soil water (e.g., $-4$ to $0 \degree C$) where rapid phase change occurs. In addition, measured $\lambda_{eff}$ data are few compared to other physical properties. Therefore, many FSTC algorithms have been developed and a few of them have been incorporated in numerical simulation programs for calculating $\lambda_{eff}$. However, large discrepancies between simulated and observed soil thermal regimes have been reported. Previous studies either evaluated the performance of a few FSTC algorithms with limited $\lambda_{eff}$ or simply compared the performance of the algorithms in numerical simulation programs. No study has been performed to systematically assess the performance of the FSTC algorithms included in numerical simulation programs with both observations and model simulations. In this study, 14 FSTC algorithms incorporated in various numerical simulation programs were evaluated with a compiled dataset consisting of 331 $\lambda_{eff}$ measurements on 27 soils from seven studies made at temperatures on or below $-4 \degree C$. The Becker 1992 algorithm provided the best estimates of the $\lambda_{eff}$ measurements, but the accuracy of the estimates was not good (i.e., RMSE $= 0.46 W m^{-1} C^{-1}$, Bias $= -0.04 W m^{-1} C^{-1}$ and NSE $= 0.51$). These FSTC algorithms were also incorporated in the Simultaneous Heat and Water (SHAW) model to compare their effects on the simulating soil temperature and water content at two field sites with contrasting soil textures in USA. The simulation results showed that the average bias of simulated and observed soil temperature for all depths ranged from $-2.2$ to $2.8 \degree C$ and the average differences of liquid water content ranged from $-0.08$ to $0.1 cm^{-3}$ $cm^{-3}$. Generally no FSTC algorithm combined with the SHAW model satisfactorily estimated the dynamic soil thermal regime. Perspectives on future studies are discussed.

1. Introduction

Effective soil thermal conductivity ($\lambda_{eff}$, $W m^{-1} C^{-1}$) is a thermal property that describes the magnitude of conductive heat transfer under a unit temperature gradient. Soil thermal conductivity (STC) algorithms are required by numerical simulation programs (e.g., land surface...

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https://doi.org/10.1016/j.geoderma.2021.115207
Received 31 January 2021; Received in revised form 5 May 2021; Accepted 6 May 2021
Available online 16 May 2021
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models, hydrological models and Soil Vegetation Atmosphere Transfer-SVAT models) to estimate soil temperature or surface energy fluxes at different scales (He et al., 2018a, 2018b; Peters-Lidard et al., 1998; Verhoef, 2004; Wang et al., 2012; Yang et al., 2005, 2007), which affect different scales (He et al., 2018a, 2018b; Peters-Lidard et al., 1998; SVAT models) to estimate soil temperature or surface energy fluxes at incorporated into land surface models (He et al., 2020b; Lu et al., 2007). Regional and global climates (Ebel et al., 2019; Koster et al., 2004; Li models, hydrological models and Soil Vegetation Atmosphere Transfer-Land Model; DPHP-dual probe heat pulse; DTS-distributed temperature sensing; EC-Electrical conductivity; FSTC-frozen soil thermal conductivity algorithm; GCM-General Circulation Models; GHP-guarded hot plate; HP-heat pulse; OM-organic matter; Phase algorithms implemented in the land surface models (Luo et al., 2009b; Peters-Lidard et al., 1998; Yang et al., 2018). Few studies have used both measured values of measured soil thermal conductivity (He et al., 2021, 2020d, 2017; Tian et al., 2011; Luo et al., 2017, 2009a; Tong et al., 2016; Wang et al., 2017), no such numerical study has been performed with FSTC algorithms. Despite the evidence that soil thermal conductivity values estimated with various STC algorithms can differ from that of tabulated or measured values by up to an order of magnitude (Clark and Arritt, 1995; He et al., 2020b; Peters-Lidard et al., 1998), these algorithms continue to be used in new or upgraded land surface models. In addition, only a small portion of STC algorithms are applicable to estimate STC in frozen soils (FSTC) though numerous STC algorithms are available in literature (Bao et al., 2016; Tian et al., 2016). Moreover, even less FSTC algorithms included in numerical simulation models have been systematically evaluated in previous studies (Hu et al., 2017; Peters-Lidard et al., 1998). Although STC algorithms have been modified to improve the performance of the land surface models (Chen et al., 2012; Lawrence et al., 2011; Luo et al., 2017, 2009a; Tong et al., 2016; Wang et al., 2017), no such numerical study has been performed with FSTC algorithms. Previous studies either only evaluated STC algorithms with measured soil thermal conductivity (He et al., 2021, 2020d, 2017; Tian et al., 2016; Wang et al., 2020b, 2020c; Yan et al., 2019; Zhao and Si, 2019; Zhao et al., 2019), inversely calculated thermal conductivity from soil temperature (Du et al., 2020), or only evaluated the effects of STC algorithms in numerical simulation programs with measured temperature and water content (Luo et al., 2009b; Peters-Lidard et al., 1998; Yang et al., 2018). Few studies have used both measured values of effective soil thermal conductivity and temperature data to evaluate the STC algorithms (Dai et al., 2019; He et al., 2020b; Tong et al., 2016), and no such study has been reported to comprehensively evaluate FSTC algorithms. The performance of the FSTC algorithms to predict soil $\lambda_{eff}$ should be fully evaluated with a dataset that consists of soils with a wide

Table 1

<table>
<thead>
<tr>
<th>No.</th>
<th>Author/Source</th>
<th>Abbrev.</th>
<th>Type</th>
<th>No. of Parameters</th>
<th>Parameters</th>
<th>Numerical model incorporation</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Kersten (1949)</td>
<td>KM1949</td>
<td>Empirical-linear regression</td>
<td>2-4</td>
<td>$a_p$, $\rho_b$</td>
<td>ST&amp;TP-ES</td>
<td>Algorithm is developed based on steady-state methods; for unfrozen and frozen soils of various textures and bulk densities</td>
</tr>
<tr>
<td>2</td>
<td>de Vries (1963)</td>
<td>DV1963</td>
<td>Theoretical-discrete model</td>
<td>2-4</td>
<td>$F$, $G_b$</td>
<td>SHAW</td>
<td>For unfrozen and frozen soils of various textures and bulk densities</td>
</tr>
<tr>
<td>3</td>
<td>Johansen (1975)</td>
<td>JO1975</td>
<td>Empirical-normalized</td>
<td>2-3</td>
<td>$P$, $S_b$, $a_p$, $\rho_b$, $f_{wax}$</td>
<td>PRM, CABLE, CLASS</td>
<td>Model is developed based on steady-state data, for unfrozen and frozen soils</td>
</tr>
<tr>
<td>4</td>
<td>Farouki (1981)</td>
<td>FO1981</td>
<td>Empirical-normalized</td>
<td>2-4</td>
<td>$T$, $T_s$, $S_b$, $P_b$, $a_s$</td>
<td>GCM, CoLM, CLM, UM</td>
<td>Modified form of Johansen (1975) model, for unfrozen and frozen soils</td>
</tr>
<tr>
<td>5</td>
<td>Lunardini (1981)</td>
<td>LV1981</td>
<td>Empirical-geometric mean model</td>
<td>2-3</td>
<td>$P_1$, $a_s$</td>
<td>LSM</td>
<td>Geometric mean model for unfrozen and frozen soils</td>
</tr>
<tr>
<td>6</td>
<td>McCumber and Pielke (1981)</td>
<td>MP1981</td>
<td>Empirical</td>
<td>2-4</td>
<td>$\gamma$, $\psi_{av}$</td>
<td>CAPS, SVATS, Eta-LSS, NCEP, ECMWF, LEAF-OLAM, OSU-CAPS, WRF, Noah</td>
<td>Thermal conductivity as a function of matric potential, for unfrozen and frozen soils</td>
</tr>
<tr>
<td>7</td>
<td>Verseguy (1991)</td>
<td>VD1991</td>
<td>Empirical</td>
<td>2-4</td>
<td>$a_m$, $\theta_{av}$, $P$</td>
<td>CLASS</td>
<td>Modified form of Johansen (1975) model, for unfrozen and frozen soils</td>
</tr>
<tr>
<td>8</td>
<td>Becker et al. (1992)</td>
<td>BB1992</td>
<td>Empirical</td>
<td>2-4</td>
<td>$a_1$, $a_2$, $a_3$, $a_4$</td>
<td>SIB2</td>
<td>A model with four parameters for unfrozen and frozen gravel, gravel, sand, silt clay and peat</td>
</tr>
<tr>
<td>9</td>
<td>Desborough and Pitman (1998)</td>
<td>DP1998</td>
<td>Empirical</td>
<td>2-4</td>
<td>$P$, $\theta_{m}, \xi_{av}$, $\theta_{m, lso}$, $\theta_{m, lso}$</td>
<td>BASE</td>
<td>Modified form of Johansen (1975) model, for frozen soils</td>
</tr>
<tr>
<td>10</td>
<td>Peters-Lidard et al. (1998)</td>
<td>PL1998</td>
<td>Empirical-normalized</td>
<td>2-4</td>
<td>$a_{m, lso}$, $\theta_{av, lso}$, $P_m$</td>
<td>UM, ISBA, Noah, JULES</td>
<td>Modified form of Johansen (1975) model, for unfrozen and frozen soils</td>
</tr>
<tr>
<td>11</td>
<td>Shmakin (1998)</td>
<td>SA1998</td>
<td>Empirical-normalized</td>
<td>2-4</td>
<td>$a_{m, lso}$, $\theta_{av, lso}$, $P_m$</td>
<td>SPONSOR</td>
<td>Modified form of Johansen (1975) model, for unfrozen and frozen soils</td>
</tr>
<tr>
<td>13</td>
<td>Lawrence and Slater (2008)</td>
<td>LS2008</td>
<td>Empirical-normalized</td>
<td>2-4</td>
<td>$f_{soil}$</td>
<td>CLM</td>
<td>Modified form of Johansen (1975) model by including effects of organic matter</td>
</tr>
</tbody>
</table>

Abbreviations: CANL-Canadian Land Surface Scheme; CLASS-Community Land Model; CLM-Community Land Model; DPHP-dual probe heat pulse; DTS-distributed temperature sensing; EC-Electrical conductivity; FSTC-frozen soil thermal conductivity algorithm; GCM-General Circulation Models; GHP-guarded hot plate; HP-heat pulse; OM-organic matter; Phase-solids, air, liquid water, ice; PRM-Purdue Regional Model; SCA-self-consistent approximation; SHAW-Simultaneous heat and water; SIB2-Simple Biosphere Model; SHPF-single probe heat pulse; SPONSOR-Semi-distributed Parameterization Scheme of the ORography-induced hydrology; STC-soil thermal conductivity algorithm; SVATS-Soil Vegetation Atmosphere Scheme.
range of soil textures, levels of water saturation, and subfreezing temperatures. Further, field measurements combined with model simulations are required to test the effects of FSTC algorithms on the simulated soil thermal regime.

The objectives of this study were to (1) compare FSTC estimated $\lambda_{\text{eff}}$ values to measured $\lambda_{\text{eff}}$ values, and (2) combine the FSTC algorithms into a numerical simulation model, the Simultaneous Heat and water (SHA) model (Flerchinger, 2000; Flerchinger and Saxton, 1989), to determine how well simulated soil temperature and water content matched to measured soil temperature and water content.

2. Material and methods

2.1. A review of FSTC algorithms

A brief description of the 14 FSTC algorithms that have been incorporated in various numerical simulation programs is presented in Table 1. The FSTC algorithms vary in complexity and application. Nine of the 14 FSTC algorithms (e.g., JO1975, FO1981, DI1991, DP1998, PL1998, SA1998, CK2005, LS2008 and LS2009) interpolate $\lambda_{\text{eff}}$ at any water content or temperature based on the dry soil and saturated soil thermal conductivity values. The remaining algorithms consist of three empirical, linear/non-linear regression algorithms (i.e., KM1994, MP1998 and BB1992), one theoretical algorithm (i.e., DV1963), and one geometric mean model (LV1981). More details on the algorithms can be found in Table 1 and the supplementary file 1.

2.2. SHAW model

The SHAW (Simultaneous Heat and Water) model is a one-dimensional, finite difference model that simulates a wide range of coupled processes and properties. Heat and water fluxes (i.e., long-wave radiation exchange, absorbed solar radiation, and turbulent transfer of vapor and heat) for the atmosphere-plant-snow-residue-soil system are calculated using the coupled processes and properties. Heat and water fluxes (i.e., long-wave radiation exchange, absorbed solar radiation, and turbulent transfer of vapor and heat) for the atmosphere-plant-snow-residue-soil system are calculated using the coupled processes and properties.

Table 2
Selected soil physical properties for the evaluation of 14 frozen soil thermal conductivity algorithms.

<table>
<thead>
<tr>
<th>No.</th>
<th>Literature source</th>
<th>Soil Name</th>
<th>Soil Texture</th>
<th>Particle density (g cm$^{-3}$)</th>
<th>Bulk Density (g cm$^{-3}$)</th>
<th>Temp Range (°C)</th>
<th>$\Theta_{\text{total}}$ (cm$^3$)</th>
<th>No of Meas.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Kersten (1949)</td>
<td>Dakota sandy loam</td>
<td>Sand 0.69</td>
<td>2.71</td>
<td>1.03-2.19</td>
<td>-4</td>
<td>0.03-0.32</td>
<td>16</td>
</tr>
<tr>
<td>2</td>
<td>Kersten (1949)</td>
<td>Fairbanks silty clay loam</td>
<td>Silt 0.20</td>
<td>2.71</td>
<td>0.92-1.63</td>
<td>-4</td>
<td>0.03-0.47</td>
<td>17</td>
</tr>
<tr>
<td>3</td>
<td>Kersten (1949)</td>
<td>Northway silt loam</td>
<td>Clay 0.22</td>
<td>2.70</td>
<td>1.20-1.82</td>
<td>-4</td>
<td>0.02-0.35</td>
<td>11</td>
</tr>
<tr>
<td>4</td>
<td>Kersten (1949)</td>
<td>Ramsey sandy loam</td>
<td>Sand 0.04</td>
<td>2.71</td>
<td>1.40-2.02</td>
<td>-4</td>
<td>0.04-0.32</td>
<td>14</td>
</tr>
<tr>
<td>5</td>
<td>Penner (1970)</td>
<td>Soil #1</td>
<td>Silt 0.32</td>
<td>1.97</td>
<td>1.66-1.89</td>
<td>-5, -15</td>
<td>0.10-0.26</td>
<td>6</td>
</tr>
<tr>
<td>6</td>
<td>Penner (1970)</td>
<td>Soil #2</td>
<td>Clay 0.65</td>
<td>1.97</td>
<td>1.73-1.93</td>
<td>-5, -15</td>
<td>0.10-0.25</td>
<td>6</td>
</tr>
<tr>
<td>7</td>
<td>Penner (1970)</td>
<td>Soil #3</td>
<td>Clay 0.22</td>
<td>1.97</td>
<td>1.71-1.97</td>
<td>-5, -15</td>
<td>0.07-0.20</td>
<td>6</td>
</tr>
<tr>
<td>8</td>
<td>Penner (1970)</td>
<td>Soil #4</td>
<td>Clay 0.22</td>
<td>1.97</td>
<td>1.61-1.79</td>
<td>-5, -15</td>
<td>0.10-0.30</td>
<td>6</td>
</tr>
<tr>
<td>9</td>
<td>Penner (1970)</td>
<td>Soil #5</td>
<td>Clay 0.06</td>
<td>1.97</td>
<td>1.69-1.86</td>
<td>-5, -15</td>
<td>0.08-0.25</td>
<td>6</td>
</tr>
<tr>
<td>10</td>
<td>Penner (1970)</td>
<td>Soil #6</td>
<td>Clay 0.06</td>
<td>1.97</td>
<td>1.64-1.83</td>
<td>-5, -17</td>
<td>0.11-0.26</td>
<td>6</td>
</tr>
<tr>
<td>11</td>
<td>Penner (1970)</td>
<td>Soil #7</td>
<td>Clay 0.27</td>
<td>1.97</td>
<td>1.97-2.07</td>
<td>-5, -16</td>
<td>0.09-0.26</td>
<td>6</td>
</tr>
<tr>
<td>12</td>
<td>Penner (1970)</td>
<td>Soil #8</td>
<td>Clay 0.47</td>
<td>1.97</td>
<td>1.39-1.57</td>
<td>-6, -15</td>
<td>0.08-0.30</td>
<td>6</td>
</tr>
<tr>
<td>13</td>
<td>Penner (1970)</td>
<td>Soil #9</td>
<td>Clay 0.00</td>
<td>1.97</td>
<td>1.43-1.64</td>
<td>-6, -15</td>
<td>0.08-0.29</td>
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<tr>
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<td>Penner (1970)</td>
<td>Soil #10</td>
<td>Clay 0.00</td>
<td>1.97</td>
<td>1.40-1.63</td>
<td>-5 to -26</td>
<td>0.10-0.33</td>
<td>8</td>
</tr>
<tr>
<td>15</td>
<td>Tian et al. (2015)</td>
<td>Sandy loam</td>
<td>Clay 0.80</td>
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<td>1.30</td>
<td>-5 to -10</td>
<td>0.16-0.29</td>
<td>19</td>
</tr>
<tr>
<td>16</td>
<td>Tian et al. (2015)</td>
<td>Silt loam</td>
<td>Clay 0.15</td>
<td>2.65</td>
<td>1.30</td>
<td>-6 to -10</td>
<td>0.14-0.28</td>
<td>18</td>
</tr>
<tr>
<td>17</td>
<td>Tian et al. (2015)</td>
<td>Silty clay</td>
<td>Clay 0.17</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
</tr>
<tr>
<td>18</td>
<td>Tian et al. (2016)</td>
<td>Clay</td>
<td>Clay 0.17</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
</tr>
<tr>
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<td>Clay</td>
<td>Clay 0.16</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
</tr>
<tr>
<td>20</td>
<td>Tian et al. (2016)</td>
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<td>Clay 0.17</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
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<tr>
<td>21</td>
<td>Tian et al. (2016)</td>
<td>Sand</td>
<td>Clay 0.94</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
</tr>
<tr>
<td>22</td>
<td>Tian et al. (2016)</td>
<td>Clay</td>
<td>Clay 0.17</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
</tr>
<tr>
<td>23</td>
<td>Suzuki et al. (2002)</td>
<td>Hokudai soil (volcanic ash)</td>
<td>Clay 0.45</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
</tr>
<tr>
<td>24</td>
<td>Suzuki et al. (2002)</td>
<td>Kuroboku soil (volcanic ash)</td>
<td>Clay 0.51</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
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<td>25</td>
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<td>1.30</td>
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<td>0.13-0.28</td>
<td>18</td>
</tr>
<tr>
<td>26</td>
<td>Lu et al. (2018)</td>
<td>Aeolian sand</td>
<td>Clay 0.88</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
</tr>
<tr>
<td>27</td>
<td>Zhang et al. (2018)</td>
<td>Silty clay</td>
<td>Clay 0.39</td>
<td>2.65</td>
<td>1.30</td>
<td>-5 to -10</td>
<td>0.13-0.28</td>
<td>18</td>
</tr>
</tbody>
</table>

Note: Soil texture sizes: sand (0.005-0.05 mm), silt (0.05-0.002 mm), clay (<0.002 mm); soil #6 contains 0.48 gravel and soil #7 contains 0.17 gravel for data of Penner (1970); Kersten (1949) measured by steady-state method and the other were measured with transient methods.
reliable and reproducible experimental techniques/setup: \( \lambda_{\text{eff}} \) were measured on soil samples with transient heat pulse or steady-state method (e.g., heat pulse method (Bristow, 1998; Wang et al., 2020a), or guarded heat plate) and the measurements were made at temperature \( \leq -4 ~\circ C \). Measured \( \lambda_{\text{eff}} \) at \(-4 ~\circ C \) or below is less likely to be affected by measurement error resulting from ice melting and refreezing during the measurement when measured (He et al., 2015, 2018b; Kojima et al., 2016, 2018; Overduin et al., 2006); (2) detailed descriptions of the specimen preparation and complete soil information of textual information (i.e., contents of sand-\( f_{\text{sand}} \), silt-\( f_{\text{silt}} \) and clay-\( f_{\text{clay}} \)), porosity (P), bulk density (\( \rho_b \)), and particle density (\( \rho_p \)); (3) sufficient sample size and range of \( \theta_{\text{final}} \) at subfreezing temperatures.

The collated data pool consists of 331 measurements on 27 soils from seven studies (Kersten, 1949; Lu et al., 2018; Penner et al., 1975; Suzuki et al., 2002; Tian et al., 2015, 2016; Zhang et al., 2018). Selected soil physical properties can be found in Table 2. Readers are referred to the respective papers for additional details on soils and methodologies.

### 2.3.2. Quartz content (\( f_{\text{quartz}} \))

Quartz content significantly affects \( \lambda_{\text{eff}} \) (He et al., 2020d; Tarnawski et al., 2012) and it is required significantly by the FSTC algorithms. However, a measurement of \( f_{\text{quartz}} \) requires specific instruments, and limited information is available for \( f_{\text{quartz}} \) values (He et al., 2020c; Tarnawski et al., 2012). Compared to the usual assumptions of \( f_{\text{quartz}} = f_{\text{sand}} \text{ or } f_{\text{quartz}} = 0.5f_{\text{sand}} + f_{\text{clay}} \), some investigations found that letting \( f_{\text{quartz}} = 0.5f_{\text{sand}} \) was a more satisfactory approximation (Chen et al., 2012; He et al., 2021; Lu et al., 2007; Petersilidou et al., 1998). This approximation was adopted in this study for algorithms where quartz content was required.

### 2.3.3. Liquid water content (\( \theta_{\text{lw}} \))

Measurement of \( \theta_{\text{lw}} \) requires special equipment such as nuclear magnetic resonance (Ollitrant and Tice, 1982; Smith and Tice, 1988; Watanabe and Wake, 2009), gas dilatometry (Spaans and Barker, 1995) or differential scanning calorimetry (Ollitrant and Tice, 1982). Data containing both \( \lambda_{\text{eff}} \) and \( \theta_{\text{lw}} \) are rare as stated in section 2.3.1. Therefore, two scenarios were considered in this study: (1) all water became ice (\( \theta_{\text{ice}} = 1.09 \theta_{\text{total}}, \theta_{\text{lw}} = 0 \)) at temperatures \( \leq -4 ~\circ C \) and (2) \( \theta_{\text{lw}} \) was estimated by the Saxton et al. (1986) method:

\[
\psi = \psi_{\text{sat}} - \frac{\sqrt{g}}{\sqrt{15}} \left( T - 0.62 \right), \quad \text{where} \quad A = \psi, \beta = \psi_{\text{sat}}
\]

Rearranging Eq. (1) gave

\[
\theta_{\text{lw}} = \exp[\ln(\psi/A)/b]
\]

where \( \psi \) is matric potential calculated by the modified Clausius-Clapeyron equation (Kojima et al., 2018; Kurylyk and Watanabe, 2013)

\[
\psi = \frac{L_f}{g} \left( \frac{T}{273.15} \right)
\]

where \( L_f \) is latent heat of water fusion (3.344 \times 10^5 \text{ J kg}^{-1}), \( g \) is gravitational acceleration (9.8 m s^{-2}), and \( T \) is soil temperature (\circ C); \( A \) (Mpa) and \( b \) are empirical coefficients that can be related to soil texture (Saxton et al., 1986)

\[
A = 0.1 \exp\left( -4.396 - 7.15f_{\text{clay}} - 4.880f_{\text{sand}}^2 - 42.85f_{\text{clay}}^2 f_{\text{sand}} \right)
\]

\[
b = -3.140 - 22.2f_{\text{clay}}^2 - 34.84f_{\text{sand}}^2 f_{\text{clay}}
\]

where the value of 0.1 in Eq. (3) was used to convert unit bar to MPa.

It should be noted that the Saxton et al. (1986) method determines \( \theta_{\text{lw}} \) from soil temperature and texture, and sometimes it gives unreasonable estimation of \( \theta_{\text{lw}} \) (e.g., negative values, larger or smaller than reasonable values). For negative values or \( \theta_{\text{lw}} > \theta_{\text{total}} \), \( \theta_{\text{lw}} \) was constrained to be between 0 and \( \theta_{\text{total}} \). Not all FSTC algorithms (i.e., KIM1949, LV1981, MP1981, BB1991, B1992, SA1998, and CK2005) require the input of \( \theta_{\text{lw}} \), and these algorithms will not be affected by \( \theta_{\text{lw}} \).

### 2.4. In situ measurements for SHAW simulations

For the SHAW simulations, data from the Orchard Field Test Site located in south-western Idaho, USA (43° 19’ N, 115° 59’ W) from day 309 of 1997 (Nov. 5) to day 308 of 1998 (Nov. 4) were used. The site consisted of three microclimatic monitoring plots that were within 400 m of each other, but with different soil textures (i.e., site A: Tindahay loamy sand, site B: Tindahay sandy loam, and site C: Lankbush silt loam, uniform in the profile). Each monitoring plot was relatively flat and consisted of six subplots arranged in a circle: three subplots with bare soil were alternated with three subplots with annual cheatgrass (Bromus tectorum L.) cover. The sites were originally designed to simulate and assess effects of soil water dynamics on seedling germination (Hardegree et al., 2010). This study focuses on the bare soil subplots of site A (loamy sand) and C (silt loam). Selected soil properties are presented in Table 3.

A standard weather station was used to collect weather data including hourly precipitation (mm), air temperature (\( T_{\text{air}}, \circ C \)), wind speed (m s^{-1}), solar radiation (\( R_s, \text{ W m}^{-2} \)), and humidity (%). Temperature often dropped below 0 \circ C in winter and the minimum observed \( T_{\text{air}} \) during the period was -15 \circ C, so that the soil experienced a number of freezing and thawing events. Soil temperature (\( T_{\text{soil}}, \circ C \)) was recorded hourly with thermocouples at depths of 1, 2, 5, 10, 20, 30, 50, 75 and 100 cm in each subplot. Soil water contents measured with 3-rod TDR sensors were recorded every other hour at the same depths as soil temperature except for the 1 cm depth. Basic soil properties (e.g., soil texture and bulk density) of the site were measured in a standard way and all observations went through strict quality control. Additional details on the site description, instrumentation, and sampling details were reported (Flerchinger et al., 2012; Flerchinger and Hardegree, 2004).

### 2.5. Performance metrics

The calculated and measured \( \lambda \) values were plotted against each other to visually assess how well the estimated and measured \( \lambda_{\text{eff}} \) values matched on 1:1 plots. Three performance metrics were also used, including (1) root mean square error (RMSE), (2) Bias, and (3) Nash-Sutcliffe Efficiency (NSE)

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (M_i - P_i)^2}{n}}
\]

\[
\text{Bias} = \frac{1}{n} \sum_{i=1}^{n} (P_i - M_i)
\]
Table 4
Performance metrics for the ability of the 14 thermal conductivity algorithms to estimate frozen soil thermal conductivity, when liquid water content is assumed to equal zero and when liquid water content is calculated by the method of Saxton et al. (1986).

<table>
<thead>
<tr>
<th>No.</th>
<th>Source</th>
<th>Abbrev.</th>
<th>( \theta_{lw} = 0 )</th>
<th>Bias (W m(^{-1}) C(^{-1}))</th>
<th>NSE</th>
<th>RMSE (W m(^{-1}) C(^{-1}))</th>
<th>Bias (W m(^{-1}) C(^{-1}))</th>
<th>NSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Kersten (1949)</td>
<td>KM1949</td>
<td>0.93</td>
<td>−0.48</td>
<td>−1.05</td>
<td>0.93</td>
<td>−0.48</td>
<td>−1.05</td>
</tr>
<tr>
<td>2</td>
<td>de Vries (1963)</td>
<td>DV1963-</td>
<td>0.75</td>
<td>0.55</td>
<td>−0.35</td>
<td>0.87</td>
<td>0.74</td>
<td>−0.81</td>
</tr>
<tr>
<td>3</td>
<td>Johansen (1975)</td>
<td>JO1975+</td>
<td>0.60</td>
<td>0.17</td>
<td>0.15</td>
<td>0.58</td>
<td>−0.06</td>
<td>0.19</td>
</tr>
<tr>
<td>4</td>
<td>Farouki (1981)</td>
<td>FO1981+</td>
<td>1.34</td>
<td>−0.96</td>
<td>−3.28</td>
<td>1.11</td>
<td>0.61</td>
<td>−1.91</td>
</tr>
<tr>
<td>5</td>
<td>Lunardini (1981)</td>
<td>LV1981+</td>
<td>1.25</td>
<td>0.73</td>
<td>−2.69</td>
<td>1.18</td>
<td>0.65</td>
<td>−2.29</td>
</tr>
<tr>
<td>7</td>
<td>Venechegy (1991)</td>
<td>VD1991+</td>
<td>1.16</td>
<td>1.05</td>
<td>−2.18</td>
<td>0.94</td>
<td>0.80</td>
<td>−1.12</td>
</tr>
<tr>
<td>8</td>
<td>Becker et al. (1992)</td>
<td>BB1992</td>
<td>0.46</td>
<td>−0.04</td>
<td>0.51</td>
<td>0.46</td>
<td>−0.04</td>
<td>0.51</td>
</tr>
<tr>
<td>9</td>
<td>Desborough and Pitman (1998)</td>
<td>DP1998-</td>
<td>0.77</td>
<td>0.29</td>
<td>−0.42</td>
<td>0.81</td>
<td>0.03</td>
<td>−0.57</td>
</tr>
<tr>
<td>10</td>
<td>Peters-Lizard et al. (1998)</td>
<td>PL1998+</td>
<td>0.60</td>
<td>0.17</td>
<td>0.15</td>
<td>0.58</td>
<td>−0.06</td>
<td>0.19</td>
</tr>
<tr>
<td>11</td>
<td>Shmakin (1998)</td>
<td>SA1998</td>
<td>0.60</td>
<td>−0.12</td>
<td>0.13</td>
<td>0.61</td>
<td>−0.12</td>
<td>0.13</td>
</tr>
<tr>
<td>12</td>
<td>Côté and Conrad (2005)</td>
<td>CK2005</td>
<td>0.58</td>
<td>−0.25</td>
<td>0.20</td>
<td>0.59</td>
<td>−0.28</td>
<td>0.19</td>
</tr>
<tr>
<td>13</td>
<td>Lawrence and Slater (2008)</td>
<td>LS2008+</td>
<td>0.60</td>
<td>0.17</td>
<td>0.15</td>
<td>0.58</td>
<td>−0.06</td>
<td>0.19</td>
</tr>
<tr>
<td>14</td>
<td>Luo et al. (2009b)</td>
<td>LS2009b</td>
<td>0.58</td>
<td>0.14</td>
<td>0.20</td>
<td>0.58</td>
<td>−0.09</td>
<td>0.21</td>
</tr>
</tbody>
</table>

N\(\text{SE} = 1 / \sum_{i=1}^{n} (M_i - P_i)^2 / \sum_{i=1}^{n} (M_i - \bar{M})^2\) \hspace{1cm} (8)

where, \(M_i\) and \(P_i\) are the \(i\)th measured and predicted values, respectively; \(\bar{M}\) is mean measured values; \(n\) is the number of measured values. RMSE is absolute difference between \(M_i\) and \(P_i\), NSE = 1 indicates a perfect match between \(M_i\) and \(P_i\), NSE = 0 indicates that \(P_i\) is as accurate as \(\bar{M}\), and NSE < 0 indicates that \(\bar{M}\) is the better predictor.

3. Results and discussion
3.1. Comparisons of FSTC algorithm estimated and measured \(\lambda_{eff}\) values
3.1.1. Measured \(\lambda_{eff}\) assuming that \(\theta_{lw} = 0\)
Comparisons of measured and estimated \(\lambda_{eff}\) assuming \(\theta_{lw} = 0\) are shown in Fig. 1. The performance metrics of the 14 FSTC algorithms are tabulated in Table 4. The BB1992 algorithm gives the best estimation among the 14 investigated FSTC algorithms (RMSE = 0.46 W m\(^{-1}\) C\(^{-1}\), Bias = −0.04 W m\(^{-1}\) C\(^{-1}\) and NSE = 0.51), still fairly poor. This agrees with the study of He et al. (2020b) that showed the BB1992 algorithm outperformed other linear or non-linear regression soil thermal conductivity algorithms. However, BB1992 algorithm surprisingly has not been widely used, because its form can be easily incorporated into numerical simulations (Becker et al., 1992; He et al., 2017). It should also be noted that the BB1992 algorithm used the middle value in Table S-1 of supplementary file 1 for each soil type. It has the potential to be improved by varying the four parameters, but details on adjusting parameters is not clearly stated in the original paper.

In contrast, the most widely applied MP1981 algorithm that has been incorporated into more than nine numerical simulation programs performed the worst, because it returns a constant value of \(\lambda_{eff} = 0.171\) W m\(^{-1}\) C\(^{-1}\) at potential threshold \(\log(\Psi) > 5.1\) MPa (He et al., 2020a). The calculated potential for all data included in this study using the modified Clausius-Clapeyron equation at temperature below −4°C is greater than the potential threshold. Experimental data of \(\lambda_{eff}\) at temperature greater than −4°C were not included in this study because of the uncertainty in measurement errors (He et al., 2015, 2018b, 2017; Kojima et al., 2016, 2018; Overduin et al., 2006). A weakness of the MP1981 algorithm is that it was developed based on three unfrozen soils (i.e., clay, silt loam and fine sand) of Al-Nakshabandi and Kohne (1965) and does not account for ice content (He et al., 2020a). The other reason for the poor performance may be attributed to the MP1981 algorithm cannot represent the effects of soil texture on \(\lambda_{eff}\) potential (He et al., 2020a). Water content largely determines the magnitude of \(\lambda_{eff}\) while water contents of coarse- and fine-textured soils differ at the same matric potential. Therefore, prediction of \(\lambda_{eff}\) from only matric potential would lead to errors. The MP1981 algorithm is reported to be problematic for some unfrozen soil applications and is not verified in frozen soils (He et al., 2020a; Lu et al., 2019). However, the advantage of the MP1981 algorithm is that it connects thermal conductivity and matric potential because both of them vary with water content, which can be used to study the coupled transport of heat and water (He et al., 2020a). The matric potential based FSTC algorithm would be promising once the texture effect is accounted.

Because \(f_{sands} = 0.5\) \(f_{quarts}\) was assumed in this study (He et al., 2021; Lu et al., 2007; Peters-Lizardi et al., 1998) and the effects of organic matter were not considered (\(f_{om}\) is negligibly small), the JO1975, PL1998, and LS2008 algorithms provided the same results, and they performed modestly among the 14 FSTC algorithms investigated. The DV1963, FO1981, LV1981 and VD1991 generally overestimated \(\lambda_{eff}\) while the rest of the algorithms showed varying performances on data from different studies. It should be noted that effects of organic matter cannot be ignored for peat soil or soil with high organic matter content as thermal conductivity of organic matter is about 0.25 W m\(^{-1}\) °C\(^{-1}\), which is smaller than other soil components such as water (~0.56 W m\(^{-1}\) °C\(^{-1}\)) and soil solids (2–8 W m\(^{-1}\) °C\(^{-1}\)) (He et al., 2020b; Zhao et al., 2019).

3.1.2. Measured \(\lambda_{eff}\) with \(\theta_{lw}\) values estimated by the Saxton et al. (1986) method
Ten of the 14 FSTC algorithms (i.e., DV1963, JO1975, FO1981, LV1981, VD1991, DP1998, PL1998, CK2005, LS2008 and LS2009) require the input of \(\theta_{lw}\) while the remaining four (i.e., KM1949, MP1981, BB1992 and SA1998) are not affected by changes in \(\theta_{lw}\). Comparisons of measured and estimated \(\lambda_{eff}\) values were made when \(\theta_{lw}\) was calculated with the Saxton et al. (1986) method, but the inclusion of \(\theta_{lw}\) did not significantly change the performance of the algorithms as shown in Fig. 2 compared to that in Fig. 1. Table 4 shows that inclusion...

For some conditions the Saxton et al. (1986) method provides unreasonable estimates of $\theta_{lw}$, because it does not consider the effects of total water content ($\theta_{total}$) (He and Dyck, 2013; He et al., 2016). For instance, the largest $\theta_{lw}$ value (0.04 cm$^3$ cm$^{-3}$) was found in Aeolian sand with zero clay content of Lu et al. (2018) at 20$^\circ$C, and the calculated $\theta_{lw}$ value was the same for samples for every $\theta_{total}$. Unreasonable estimates of $\theta_{lw}$ with the Saxton et al. (1986) method were also reported elsewhere (Tian et al., 2016). The use of the Anderson and Tice (1972) approach, which estimated $\theta_{lw}$ based on temperature and soil specific surface area, resulted in $\theta_{lw}$ values equal to zero (data not shown). Direct measurements of unfrozen water content ($\theta_{lw}$) require special equipment such as nuclear magnetic resonance (Oliphant and Tice, 1982; Smith and Tice, 1988; Watanabe and Wake, 2009), gas dilatometry (Spaans and Baker, 1995) or differential scanning calorimetry (Oliphant and Tice, 1982). Because datasets containing measurements of both $\lambda_{eff}$ and $\theta_{lw}$ are rare, mathematical algorithms are often used to estimate values of $\theta_{lw}$ (Kurylyk and Watanabe, 2013). To increase the performance of FSTC algorithms, more paired measurements on $\lambda_{eff}$ and $\theta_{lw}$ are required.

### 3.2. SHAW model simulations

#### 3.2.1. Simulated results for sites A and C

The SHAW model simulations of $T_{soil}$ and $\theta_{lw}$ at Site A, the loamy sand, at selected depths in the 0–4 m soil profile are presented in Figs. 3 and 4, respectively. The simulated and observed $T_{soil}$ and $\theta_{lw}$ values for Site C are presented in Figs. 5 and 6, respectively. $T_{soil}$, $\theta_{total}$ and $\theta_{lw}$ values were observed from October to April. The observed air temperature and/or precipitation are also superimposed on Figs. 3 to 6. Soil water and temperature values were monitored in the 0–1 m layer, while the SHAW model simulated $T_{soil}$, $\theta_{total}$ and $\theta_{lw}$ in the 0–4 m layer. It should be noted that no parameter optimization process was performed during the SHAW modeling in order to evaluate the influence of different FSTC algorithms. In all cases the initial condition was set as the measured soil temperature and water content values, and the soil surface driving forces were derived from the weather observations, including air temperature, humidity, wind, solar radiation, and precipitation.

The KM1949 algorithm performed notably different in the temperature simulations of both sites A and C compared to the other 13 algorithms (Figs. 3 and 5). The KM1949 underestimated the penetration of frost depth in winter, and a smaller summer rise in soil temperature was simulated. These responses are characteristic of thermal conductivity.
being too small. They are consistent with Figs. 1 and 2, in which KM1949 is the only algorithm to drastically underestimate $\lambda_{\text{eff}}$ for certain data sets. For either Site A or C, the simulated $\theta_{\text{total}}$ and $\theta_{\text{lw}}$ values are similar for all 14 FSTC algorithms, and the simulated values are smaller than the measured values during the winter time (Figs. 4 and 6). The consistent bias in $\theta_{\text{total}}$ and $\theta_{\text{lw}}$ derived from all of the FSTC algorithms may be caused by a bias in the soil water retention curve parameters leading to inaccuracies in simulating the soil water dynamics. Similar values of $\theta_{\text{total}}$ and $\theta_{\text{lw}}$ for all of the FSTC algorithms suggest that differences in thermal conductivity mainly affect $T_{\text{soil}}$ with only limited effects on $\theta_{\text{total}}$ or $\theta_{\text{lw}}$ that is calculated from the modified Clausius-Clapeyron equation. Developing FSTC algorithms that connect thermal conductivity and matric potential for frozen soil applications is highly recommended, because they will provide further opportunities to study coupled water and heat transfer (He et al., 2020a).

3.2.2. Comparison of simulated and measured results

The differences between the simulated and measured $T_{\text{soil}}$ and $\theta_{\text{lw}}$ within the top 1 m of the soil profile at Sites A and C are illustrated in Figs. 7 and 8, respectively. The differences between the observed and simulated results between October and April were shown, because the observations were available during this period of time. The green color indicates zero or small differences between the simulated and observed values of $T_{\text{soil}}$ and $\theta_{\text{lw}}$, while yellow and red indicate overestimations and blue indicates underestimations.

As can be seen from Fig. 7, The KM1949 algorithm gave the worst values of simulated $T_{\text{soil}}$ at all depths, as indicated by the wide distribution (i.e., 25–75% of the boxplot). Somewhat poor estimations of $T_{\text{soil}}$ for all 14 algorithms occurred in the 0–10 cm soil layer, as there was a wide distribution and more outliers compared to depths at 20 cm and below. At site A (loamy sand), generally all 14 algorithms (except MP1981) overestimated $T_{\text{soil}}$ in the 0–5 cm layer and underestimated $T_{\text{soil}}$ at depths below 10 cm. Estimation of $T_{\text{soil}}$ for most of the 14 algorithms was worse at depths below 10 cm at Site A than at Site C (silt loam). All 14 algorithms underestimated $T_{\text{soil}}$ at all Site C depths (Fig. 7). This agrees with the results in section 3.1, where most of the 14 FSTC algorithms overestimated $\lambda_{\text{eff}}$ of the fine-textured soils (e.g., silty clay from the study of Zhang et al. (2018), but underestimated $\lambda_{\text{eff}}$ of the coarse-textured soils (e.g., Aeolian sand from study of Lu et al. (2018)). This indicated that the evaluation of the FSTC algorithms with measured values could provide guidance in the selection of FSTC algorithms to be incorporated into numerical simulation programs.

For simulated versus measured $\theta_{\text{lw}}$ values, all 14 algorithms performed similarly for each site, but the algorithms that performed better for the 0–50 cm layer at site A performed poorly at the 75 and 100 cm depths compared to Site C. For both sites, $\theta_{\text{lw}}$ values were overestimated.
at shallow depths and underestimated at deeper depths (Fig. 8). At site A, $\theta_{lw}$ values at the 2 cm depth were generally overestimated, and the lower depths were underestimated. The $\theta_{lw}$ values in the 0–20 cm layer were overestimated and underestimated in deeper soil at Site C. Although soil texture was uniform at depths below 75 cm for both sites, the bias between estimated and observed $T_{soil}$ and $\theta_{lw}$ differed with depth. The underlying reason is unknown, but it may be caused by error propagation from the top soil layer due to parameterization related processes (Clark et al., 2008; Duan et al., 2006; Kavetski et al., 2006; Wagener and Wheater, 2006).

The average bias of $T_{soil}$ for all depths ranges from 2.2 to 2.8 $^\circ$C, and the average differences of $\theta_{lw}$ range from 0.08 to 0.1 cm$^3$ cm$^{-3}$. Other studies report that selection of STC algorithms may result in simulated temperature errors up to 3 $^\circ$C (He et al., 2020b; Luo et al., 2009b; Peters-Lidard et al., 1998; Yang et al., 2018). Previous studies only focus on the top 1 or 2 shallow depths, while our results show that bias in $T_{soil}$ and $\theta_{lw}$ is more significant at shallow depths than in deeper soil. In addition, a few studies (Dai et al., 2019; Hu et al., 2017; Luo et al., 2009b; Peters-Lidard et al., 1998; Zhang et al., 2012) aimed to assess the effects of STC algorithms on ground temperature changes, but few (Dai et al., 2019; Hu et al., 2017; Luo et al., 2009a) focused on or included the wintertime soil thermal regime. There are three studies investigating the Tibetan plateau by incorporating STC algorithms into the Common Land Model (CoLM). Luo et al. (2009b) indicated that simulated temperature errors with the LS2009 algorithm were as large as 3 $^\circ$C. Hu et al. (2017) evaluated the algorithms of JO1975, FO1981 and Luo et al. (2009b). Their results showed that the JO1975 algorithm performed well in frozen soils, while the LS2009 algorithm performed well in unfrozen soils. Dai et al. (2019) incorporated seven STC algorithms (i.e., DV1963, JO1975, JO1975, FO1981, CK2005, and three algorithms for unfrozen soils (Balland and Arp, 2005; Lu et al., 2007; Tarnawski and Leong, 2012)) in the CoLM. They showed that the modified Balland and Arp (2005) algorithm gave the best estimations of thermal conductivity and soil temperature. However, our study demonstrated that no FSTC algorithms satisfactorily simulated soil temperature and liquid water content. Therefore, further development of the FSTC algorithm valid for additional applications is required.

4. Conclusions and perspectives

In this study, 14 frozen soil thermal conductivity (FSTC) algorithms that have been incorporated into various numerical simulation programs were evaluated by comparing their estimated $\lambda_{eff}$ values to measured $\lambda_{eff}$ values. The FSTC algorithms were also incorporated into the Simultaneous Heat and Water (SHAW) model to simulate soil temperature ($T_{soil}$) and liquid water content ($\theta_{lw}$), which were compared to...
observed values from two field research sites established by the USDA-ARS, Northwest Watershed Research Center, Idaho, USA. The results show that BB1992 algorithm (Becker et al., 1992) provided the best estimates, but it was not altogether satisfactory (i.e., RMSE = 0.46 W m⁻¹ °C⁻¹, Bias = -0.04 W m⁻¹ °C⁻¹ and NSE = 0.51). The inclusion of θlw in partially frozen soil, rather than assuming that all of the water was ice, slightly improved the performances of the FSTC algorithms. FSTC algorithms that performed relatively well on estimating λeff may not have necessarily performed very well on estimating Tsoil and θlw when used in a numerical simulation model, but the overall results provided evaluation information on the FSTC algorithms. The SAHW simulation results showed that the average bias of simulated and observed soil temperature for all depths ranges from -2.2 to 2.8 °C, and the average differences of liquid water content ranged from 0.08 to 0.1 cm³ cm⁻³. Generally no FSTC algorithm could be used to satisfactorily model dynamic soil thermal regimes, with average bias of Tsoil for all depths ranges from -2.2 to 2.8 °C. Only a few of the FSTC algorithms have been incorporated into numerical simulation models to estimate soil temperature or surface energy fluxes. Additional studies are required to determine how to effectively revise specific FSTC algorithms, or develop new FSTC algorithms with improved accuracy and wider applications. Moreover, there are various numerical programs that differ in aspects such ad conceptualization, structure and parameterization but limited number of such software tools (e.g., community land model-CLM and SHAW) were investigated. Similar to the projects of PILPS (the Project for Intercomparison of Land Surface Parameterization Schemes) (Henderson-Sellers et al., 1995) and CMIP6-LS3MIP (the sixth phase of the Coupled Model Intercomparison Project-Land Surface, Snow and Soil Moisture Model Intercomparison Project) (Van Den Hurk et al., 2016) projects, a systematic and comprehensive evaluation of the mainstream software tools is recommended by incorporating these FSTC algorithms to deepen our understanding on the influence of soil thermal conductivity and the numerical programs.

5. Data availability

Datasets (measurements of soil thermal conductivity) used for in this study were digitized from the literature or obtained by personal communication, and the in-situ measurements used for SHAW model comparisons were provided by Dr. Gerald N. Flerchinger.

Author contributions

HH initiated the study and wrote the paper; GF wrote and edited the SHAW codes; YK ran the SHAW simulations; DH did the calculations and prepared the figures and Tables; HH, JW, MD, JL, RH, SH, BS, YK and GF reviewed the manuscript. All authors contributed to the discussions and provided feedback on the final version.

Declaration of Competing Interest

The authors declare that they have no known competing financial
interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Funding for this research was provided in part by Natural Sciences Foundation of China (NSFC, Grant No. 41877015 and 42077135), Natural Sciences Foundation of Shaanxi Province (2020JM-169), China Postdoctoral Science Foundation (2018M640124), State Key Laboratory of Frozen Soil Engineering (SKLFSE201905), the Youth Talent Training Program of the Northwest A&F University, and the 111 Project (No. B12007). The authors also greatly appreciate the valuable and insightful comments from the Editor Cristine Morgan and two anonymous reviewers.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gedima.2021.115207.

References


Farouki, O.T., 1981. The thermal properties of soils in cold regions. 0165-232X.

Farouki, O.T., 1981. The thermal properties of soils in cold regions. 0165-232X.

Farouki, O.T., 1981. The thermal properties of soils in cold regions. 0165-232X.


Farouki, O.T., 1981. The thermal properties of soils in cold regions. 0165-232X.

Farouki, O.T., 1981. The thermal properties of soils in cold regions. 0165-232X.

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