Impacts of different spatial temperature interpolation methods on snowmelt simulations

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Abstract:

Spatial interpolation methods can be used to estimate high density air temperature data to drive the temperature index model used to simulate snowmelt processes. Thus, evaluating the impact of different spatial temperature interpolation methods on snowmelt simulations is necessary. This study creates three air temperature datasets based on different methods for a data sparse basin. These datasets include: 1) an inverse distance weighting (IDW) method; 2) an improved IDW method considering the elevation influence on temperature; and 3) combined use of linear regression and MODIS Land Surface Temperature (LST) data. The datasets are verified at observation stations and applied to a snowmelt hydrologic model using the Soil Water Assessment Tool. The simulation results are compared with observed discharge data and uncertainties discussed.

Verification at the observation stations indicates that all datasets can reflect station air temperature. Model simulations and uncertainty analysis show that the dataset created by combined use of linear regression and MODIS LST data achieved the best simulation results and smallest uncertainties. The results also indicate that this dataset can accurately and stably reflect the spatial variation of air temperature compared with other data.

KEYWORDS air temperature data; land surface temperature; MODIS; snowmelt; spatial interpolation; SWAT

INTRODUCTION

Snowmelt is one of the most important hydrologic processes in mid- and high-latitude regions (Adam *et al.*, 2009; Edwards *et al.*, 2007) and is recognized as one of the main water sources and a significant factor influencing nutrient transport in river channels during spring (Brooks *et al.*, 1998; Stewart *et al.*, 2004). The temperature index model is a common method for simulating basin snowmelt processes because of its generally good performance and lower data requirements, despite its computational simplicity (Hock, 2003; Asaoka and Kominami, 2012). Obviously, the most important input data for this model are those of air temperature. Air temperature is a commonly observed parameter at meteorological stations. However, in data-sparse basins, the density of air temperature monitoring stations cannot meet the requirements for accurate application of the temperature index model. Thus, to create high-density and accurate air

temperature data, many data resources and methods have been developed.

Spatial interpolation is a common method for increasing data density and creating accurate air temperature data in data-sparse regions (Monestiez *et al.*, 2001; DeGaetano and Belcher, 2007). A popular spatial interpolation method is the inverse distance weighting (IDW) method (Dodson and Marks, 1997; Gemmer *et al.*, 2004). Recent developments in remote sensing techniques have fostered new data sources and methods for air temperature dataset building. With the improvement of sensors and analysis methods, various remote sensing data have been successfully used for air temperature estimation (Prihodko and Goward, 1997; Nieto *et al.*, 2011). Among these data, MODIS land surface temperature (LST) has proven useful for air temperature data creation (Sun *et al.*, 2005).

However, comparative studies of temperature building methods used to drive hydrologic models in data-sparse regions have not been comprehensive. Thus, the objective of this study is to evaluate the effects of air temperature datasets created by three different methods on snowmelt processes. This was accomplished as follows. 1) We created datasets using different methods and verified them at observation stations. 2) Then, all datasets were examined in a test basin using the Soil Water Assessment Tools (SWAT) model (Arnold and Fohrer, 2005) to simulate snowmelt processes. 3) The effects of various air temperature datasets on the simulations were analyzed as discussed below.

MATERIALS AND METHODS

Test basin

The test basin was located in the middle reach of the Amur River basin and has an area of 5,006 km² (Supplement Figure S1). The water regime of Amur River basin includes spring floods, and summer–fall floods. Spring floods are attributed to snowmelt, and summer–fall floods are related to monsoon rains in the river basin. The test basin consists of forests (90%), shrubland (6%), and farmland (4%).

Data for SWAT model

One widely used hydrologic model is the Soil Water Assessment Tool (SWAT), which was developed to predict the impact of land management practices on water, sediments, and non-point source pollution in large complex watersheds (Arnold and Fohrer, 2005). A simple but improved temperature index model was incorporated into

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SWAT to simulate snowmelt processes (Fontaine *et al.*, 2002). The introduction of this snowmelt module is described in Supplement Text S1.

The SWAT model requires a digital elevation model (DEM), soil, and land use data. A Shuttle Radar Topography Mission (SRTM) dataset was utilized for the DEM (<http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1>). Land use data were based on the Landsat TM data (Yermoshin *et al.*, 2007) of the Amur-Okhotsk project (<http://www.chikyu.ac.jp/AMORE/en08/index.html>). Soil data was obtained from the Harmonized World Soil Database (Nachtergaele *et al.*, 2012) produced by the International Institute for Applied Systems Analysis (IIASA, <http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/>). The spatial resolution of the DEM, land use data and soil data were 90 m, 30 m and 1 km, respectively.

The observed air temperature and wind speed data were acquired from the Global Historical Climate Network-Daily (GHCN-Daily, Menne *et al.*, 2012) of the National Climate Data Center (NCDC, <https://www.ncdc.noaa.gov/oa/climate/ghcn-daily/>). Daily precipitation was obtained from the Asian Precipitation Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE; Yatagai *et al.*, 2012, <http://www.chikyu.ac.jp/precip/research/>). The spatial resolution of APHRODITE data is 0.25 degree. Relative humidity and solar radiation data were from the National Centers for Environmental Predictions and Department of Energy (NCEP-DOE) Reanalysis version 2 data (Kanamitsu *et al.*, 2002, <http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.gaussian.html>); the spatial resolutions of these two datasets was 1.0 degree.

Air temperature building methods

While the IDW method has demonstrated applicability in different regions, the topographic effect on air temperature prediction should be considered, especially in mountainous areas (Garen and Marks, 2005; Stahl *et al.*, 2006). The weighted linear regression method (Thornton *et al.*, 1997; Stahl *et al.*, 2006) is a valid and common way to estimate the topographic influence on temperature data. In the rest of this paper, we call this method IDWEle (explanation of the method is provided in the Supplement Text S2).

The MODIS LST data can be used for air temperature

estimation based on the linear relationship between LST data and air temperature data at the same location. However, because the MODIS satellite operated since 1999, this method can only provide recent estimates for a limited number of years (Benali *et al.*, 2012; Yang *et al.*, 2014) and is therefore not useful for hydrological simulations based on historical observed data. In order to overcome this problem, in our prior study, Yang *et al.* (2014) proved that air temperature data can be estimated by combined use of linear regression and MODIS LST data. In the rest of this paper, we call this method LST-Linear method (explanation of this method is provided in the Supplement Text S3).

Verification of created data in observation stations

We established 10 verification stations (Supplement Figure S1a and Table I) to verify the performance of the newly created air temperature data by IDW, IDWEle, and LST-Linear methods during the snowmelt periods (April) of 1983–1987, which were also used for model operations. A search radius (200 km) was used to select the interpolation stations for the IDW and IDWEle methods. In total there were 21 observation stations used for interpolation under the IDW and IDWEle methods, including the 10 verification stations (Supplement Table SI). A verification station was not used for its own interpolation. For the LST-Linear method, stations nearest each verification station were used. Estimated daily maximum and minimum air temperature were evaluated by coefficient of determination (R^2), and root mean square error (RMSE).

Model operation and uncertainty evaluation

We ran snowmelt simulations with uncertainty analysis under four different temperature data cases: (1) based on the observed air temperature data, T-Observed. Two stations were used in the model (Station 318730 and 318780 in Supplement Figure S1a); (2) based on data from the IDW method, T-IDW; (3) based on data from the IDWEle method, T-IDWEle; (4) based on data from the LST-Linear method using MODIS LST data (MYD11A1 AQUA, 1 km, daily data in Wan, 2008), T-LST. All methods created air temperature data at the geometric center of each subbasin to perform snowmelt simulations (Supplement Figure S1b).

We conducted snowmelt simulations under all cases for the period of 1979–1987 at a daily time step. The period

Table I. Land use types used for LST-Linear method and elevations used for IDW and IDWEle methods

WMO ID	Station number*	Elevation (m)	Land Use	Land Use_LST**	IDW/IDWEle_Ave (m)***	IDWE/IDWEle_STD (m)***
318320	7	68	Wetland	Forest	109	37
318450	3	130	Forest	Wetland	116	58
318730	8	101	Wetland	Farm Land	113	62
318780	9	98	Wetland	Wetland	131	70
319130	11	88	Farm Land	Farm Land	146	125
319210	14	78	Farm Land	Farm Land	186	110
319390	9	259	Farm Land	Farm Land	121	57
319810	11	188	Farm Land	Farm Land	116	128
508880	9	83	Farm Land	Farm Land	116	52
509830	11	103	Farm Land	Wetland	116	73

* Station number stands for the number of interpolation stations used for IDW and IDWEle methods.

** Land Use_LST stands for the land use type of the nearest observation station for LST-Linear method.

*** IDW/IDWEle_Ave and IDW/IDWEle_STD respectively stand for the average elevation and the standard deviation of elevation in the interpolation stations used for IDW and IDWEle method.

1979–1982 was used as a warm-up period. Observed stream-flow data for April during 1983–1987 were obtained from the Federal Service for Hydrometeorology and Environmental Monitoring of Russia (ROSHYDROMET) and was compared with the simulation results. Nash-Sutcliffe Efficiency (*NSE*), R^2 , daily absolute error and mean absolute error (*MAE*) were used for evaluating the snowmelt simulations. In addition, the analysis of variance (*ANOVA*, $p < 0.05$) and the Steel-Dwass test ($p < 0.05$) were used for the nonparametric multiple comparisons of different input data.

This research used Sequential Uncertainty Fitting version 2 (SUFI-2) method for uncertainty analysis (Abbaspour *et al.*, 2007). In the SUFI-2 method, the Latin hypercube sampling is used to draw independent parameter sets for model operations (Abbaspour *et al.*, 2007). Supplement Table SII lists the 16 parameters needed for model operations, and Latin hypercube sampling (Abbaspour *et al.*, 2007) was used to generate 2,000 parameter sets for model operations. The parameter sets were the same in each air temperature case.

In the SUFI-2 method, a likelihood measure (*NSE*) is defined to classify model simulations into two categories: behavioral and non-behavioral (Abbaspour *et al.*, 2007). Two indices (*p-factor* and *r-factor*) are used for evaluation of simulated uncertainties, and are calculated after the behavioral simulation is selected (Abbaspour *et al.*, 2007). The parameter uncertainty is measured on the basis of proximity of the *p-factor* and *r-factor* to 1 (Yang *et al.*, 2008); the calculation methods for these two indices is introduced in Supplement Text S4.

According to the guidelines of Moriasi *et al.* (2007), runoff simulation can be judged as “satisfactory” if $NSE > 0.50$

for long-term runoff simulation under a monthly time step. In addition, Engel *et al.* (2007) pointed out that model simulation results will become poorer with a decrease in the simulation time step. Since this study adopted a daily time step for model operations, we used 0.5 as threshold to identify behavioral and non-behavioral simulations.

RESULTS AND DISCUSSION

Verification of created air temperature data

Verification of air temperature data at the 10 observation stations is shown in Table II. The average value of R^2 was greater than 0.80 for the daily maximum air temperature; this value was over 0.70 for daily minimum air temperature. The *RMSEs* were within 2.0–3.0°C for both daily maximum and minimum air temperature data. Considering the performances of R^2 and *RMSEs*, the IDW method produced relatively good results compared with other two methods.

In the IDWele method, the temperature lapse rate (TLAPS, $b_{l,d}$ of Equation (S5)) was used to estimate the effects of topography on air temperature; the average values of TLAPS are shown in Table III. Most of the TLPAS values were positive for daily maximum data and negative for daily minimum data. By using the interpolation stations (Supplement Table SI), we conducted linear regression analysis between elevation and average air temperature data. The results are shown in Supplement Figure S2. Though the *p* values were larger than 0.05, positive TLAPS and negative TLAPS could still be detected for daily maximum and minimum air temperature data, respectively (Supplement Figure

Table II. Verification of estimated air temperature (daily minimum, and maximum) at observation stations in the April during 1983–1987, by (a) R^2 , and (b) *RMSE*

(a) R^2 of each validation station							
WMO ID	IDW	Maximum IDWele	LST-Linear	IDW	Minimum IDWele	LST-Linear	
318320	0.95	0.90	0.82	0.78	0.65	0.57	
318450	0.84	0.82	0.82	0.68	0.60	0.57	
318730	0.92	0.90	0.88	0.86	0.80	0.78	
318780	0.94	0.91	0.89	0.87	0.87	0.80	
319130	0.63	0.64	0.65	0.76	0.75	0.72	
319210	0.80	0.82	0.65	0.83	0.78	0.72	
319390	0.92	0.88	0.92	0.80	0.75	0.74	
319810	0.91	0.90	0.92	0.76	0.76	0.74	
508880	0.93	0.91	0.88	0.81	0.78	0.75	
509830	0.94	0.92	0.88	0.89	0.83	0.78	
average	0.88	0.86	0.83	0.80	0.76	0.72	

(b) <i>RMSE</i> of each validation station							
WMO ID	IDW	Maximum (°C) IDWele	LST-Linear	IDW	Minimum (°C) IDWele	LST-Linear	
318320	1.27	1.86	2.97	2.54	2.85	3.72	
318450	2.55	3.07	2.85	3.66	3.82	3.63	
318730	1.66	1.84	4.66	1.60	2.07	2.57	
318780	1.58	2.11	1.98	1.83	1.75	2.35	
319130	3.64	3.77	3.21	1.81	1.92	1.96	
319210	2.65	2.55	3.40	1.58	1.79	2.04	
319390	2.37	3.29	1.84	2.88	3.10	2.72	
319810	2.53	1.94	1.86	2.17	2.09	2.47	
508880	1.75	1.94	1.96	2.03	2.18	2.35	
509830	1.42	1.60	5.12	1.26	1.64	2.34	
average	2.14	2.40	2.99	2.13	2.32	2.61	

Table III. Results of temperature lapse rates and coefficients of linear regression equations at verification stations for IDWEle and LST-Linear methods

WMO ID	IDWEle (TLAPS)		LST-Linear (first order coefficient)				LST-Linear (constant)			
	TLAPS_Max (°C/km)*	TLAPS_Min (°C/km)*	a_1 (max)	a_2 (max)	a_1 (min)	a_2 (min)	b_1 (max) (°C)	b_2 (max) (°C)	b_1 (min) (°C)	b_2 (min) (°C)
318320	-11.2	-4.9	0.99	0.99	0.92	0.99	-0.03	1.82	2.65	1.41
318450	-0.9	-3.3	0.99	0.95	1.04	0.98	0.21	-0.83	-3.06	-1.70
318730	4.8	-12.8	1.02	0.93	1.00	1.03	-0.33	-2.85	-0.99	-1.69
318780	9.6	-8.9	0.98	0.98	1.04	1.08	1.03	0.34	-0.06	-0.81
319130	1.3	-4.5	0.99	0.94	0.98	0.96	0.01	-0.47	-0.66	-0.34
319210	-0.2	-3.6	0.98	1.02	0.99	1.01	0.26	1.09	0.60	0.15
319390	14.4	2.8	1.02	0.97	1.02	1.08	-0.86	-0.77	-1.44	-2.00
319810	2.1	-4.3	0.96	0.99	0.96	0.91	0.98	1.40	1.29	1.72
508880	11.5	2.0	1.00	1.01	0.98	0.97	0.77	0.71	0.10	-0.53
509830	9.4	-6.6	0.97	1.00	0.98	0.95	0.43	4.18	0.93	1.42

* TLAPS_Max, TLAPS_Min respectively stand for the average temperature lapse rate ($b_{l,d}$ of Equation (S5)) of the daily maximum air temperature and daily minimum air temperature for IDWEle method.

Figure 1. Regression analysis between the temperature differences (b_1 and b_2) and the elevation difference in the LST-Linear method, (a) daily maximum air temperature, (b) daily minimum air temperature, (c) daily maximum LST, and (d) daily minimum LST. The stations where elevation difference is less than 10m (station: 318730, 318780, 509830) were not used for analysis

S2), and these values were consistent with the values of TLAPS listed in Table III. Moreover, the values of TLAPS (Table III) were different from the normal value ($-6.0^\circ\text{C}/\text{km}$ or $-6.5^\circ\text{C}/\text{km}$) usually adopted for interpolation (Dodson and Marks, 1997). For the IDWEle method, the accuracy of interpolation depends on the difference in elevation between the observation station and the location where one applies the IDWEle method (Thornton *et al.*, 1997; Stahl *et al.*, 2006). For the IDWEle method, elevation differences between the interpolation stations and verification stations were small (Table I) and this may lead to worse results for the IDWEle method compared with the IDW method.

For the LST-Linear method, the values of coefficients (a_1 , a_2) and constants (b_1 , b_2) of Equation (S7) and Equation (S8) are shown in Table III. The results indicate that Equation (S8) is a good approximation of Equation (S7). As the values of a_1 and a_2 were close to 1 (Table III), the differences in temperature at the two stations can be approximated using the values of b_1 and b_2 . The linear relationships between elevation differences and b_1 , b_2 are shown in Figure 1. These indicate that b_2 had a strong linear relationship with the ele-

vation difference for both daily maximum and minimum LST data, while for the b_1 , the linear relationship was insignificant for daily maximum LST data. The slopes of b_2 (Figure 1c and 1d) were $-19.0^\circ\text{C}/\text{km}$ and $-25.0^\circ\text{C}/\text{km}$ for daily maximum and minimum LST data, respectively. Different slopes were observed for b_1 (Figure 1a and 1b), the observation stations (Supplement Figure S2) and the normal value ($-6.0^\circ\text{C}/\text{km}$ or $-6.5^\circ\text{C}/\text{km}$, Dodson and Marks, 1997). The same as noted for the IDWEle method, this may lead to the worse results under the LST-Linear method.

In addition, previous studies have shown that land use type might influence air temperature estimates based on MODIS LST data (Vancutsem *et al.*, 2010; Yang *et al.*, 2014). In fact, as shown in Table I, land use type at some observation stations used for LST-Linear method were different from that of estimation stations. Although errors were larger with the LST-Linear method (Table IIb), RMSEs were within a reasonable range as compared with the latest studies in different regions based on LST data. (Shen and Leptoukh, 2011, with $2\text{--}3^\circ\text{C}$ errors; Zhu *et al.*, 2013, with $2\text{--}4^\circ\text{C}$ errors).

Figure 2. The simulated hydrograph of different air temperature cases in different years, (a) 1983, (b) 1984, (c) 1985, (d) 1986, and (e) 1987

Runoff simulation results and uncertainty analysis

The results of runoff simulations (Figures 2, 3 and 4) and uncertainty analysis (Figure 5) clearly indicate that the T-LST case can allow one to obtain better results with fewer uncertainties compared with other data.

The daily runoff simulation results for each case are shown in Figures 2 and 3. The highest R^2 and NSE were obtained from the T-LST case ($R^2 = 0.73$, $NSE = 0.72$) in all cases, while the smallest were from T-IDWEle ($R^2 = 0.51$, $NSE = 0.38$). According to the hydrograph (Figure 2), it is clear that the start of the melting period is in early April (early period, April 1st–10th) and intensification of the melting processes mainly occurs in the middle of April (middle period, April 11th–20th), while the snowmelt process is relative stable in late April (late period, April 21st–30th). In this study, the daily absolute error and MAE were calculated and $ANOVA$ analysis conducted for each period. Except the middle period ($p = 0.002$), the results were insignificant ($p > 0.05$). The Steel-Dwass test was calculated for the middle period (Figure 4). The p values between the T-LST case and the T-IDW, T-IDWEle cases were 0.02 and 0.04, respectively, which indicate that the T-LST case can produce less simulation errors than T-IDW and T-IDWEle. Though the differences between the T-LST case and T-Observed case were insignificant, the results still indicate that the $MAEs$ of T-LST case were smaller than T-Observed in every period.

In addition, the number of behavioral simulations is shown in Figure 5a. The results indicate that the T-LST case can obtain 31 behavioral simulations, which is significantly larger than others. The p -factor and r -factor (Figure 5b and 5c) also indicate that the T-LST data is more effective for reducing the uncertainty relative to the other data. Though the T-Observed case can produce relatively stable results of

Figure 3. The results of R^2 and NSE of simulated discharges under different air temperature cases

NSE and R^2 , data with low spatial density reduces reproducibility.

It is interesting that the IDWEle and IDW methods provided better results than the LST-Linear method at the verification stations (Table II), while the same methods cannot provide better snowmelt simulations. Elevation differences (Table IV) between the subbasins and their interpolation stations were larger than elevation differences between verification stations and interpolation stations (Table I). In particular, subbasins 5, 7 and 13 which constitute more than 40% of the total area (Table IV) show this tendency most clearly. Topographic correction is lacking in the IDW method, thus the performance of this method was better at the verification stations, while worse for simulating snowmelt. Since the IDWEle method relies on low-elevation stations, it may

Figure 4. Absolute error of simulated discharges for different air temperature data, (a) entire period, (b) early period (April 1st-10th), (c) middle period (April 11th-20th), and (d) late period (April 21th-30th), data labels indicate the *MAEs*. “a” and “b” indicate statistical groupings of *ANOVA* analysis and Steel-Dwass test

Table IV. Elevations of each subbasin and interpolation station of IDW and IDWEle methods

Subbasin ID	Areal Percentage (%)	Ave_Sub(m)*	L_Sub (m)*	H_Sub (m)*	STD_Sub (m)*	IDW/IDWEle_Ave (m)**	IDW/IDWEle_STD (m)**
1	3.9%	94	82	430	72	116	61
2	0.9%	146	100	533	79	120	60
3	4.2%	167	107	712	119	120	60
4	7.5%	172	100	997	121	135	64
5	6.5%	507	210	1273	193	127	68
6	5.4%	194	142	1085	166	127	68
7	3.2%	647	210	1322	212	127	68
8	3.1%	145	105	712	88	120	60
9	13.7%	354	144	1417	211	135	66
10	4.2%	194	139	777	116	120	60
11	7.2%	146	125	738	94	123	60
12	8.2%	221	139	940	117	120	60
13	32.0%	597	128	1194	195	129	66

* Ave_Sub, L_Sub, H_Sub, and STD_Sub stand for the average elevation, lowest elevation, highest elevation and standard deviation of elevation of each subbasin, respectively.

** IDW/IDWEle_Ave and IDW/IDWEle_STD respectively stand for the average elevation and standard deviation of elevation in the interpolation stations, which are used for IDW and IDWEle methods.

represent errors rather than improved snowmelt simulation.

In addition, the snowmelt simulations indicate that based only on sparsely observed air temperature data, the spatial interpolation method (IDW and IDWEle) cannot always generate accurate temperature data. In fact, the station density of the region was less than 1/20,000 km² (87 stations in 2,040,700 km²), significantly less than previous studies based on the IDW method (Courault and Monestiez, 1999, with station density 1/1,250 km²; Dodson and Marks, 1997, with station density 1/1,000 km²).

The results indicate that the data density and elevations directly limits the applicability of the IDW and IDWEle methods for driving SWAT snowmelt simulation in a data-sparse basin. Though the performance of the LST-Linear method is relatively poor at observation stations (Table II), the simulation results indicate that the data created by the LST-Linear method are stable and accurate approximations of the actual air temperature in the study basin.

Figure 5. Uncertainty analysis results of snowmelt simulations of different air temperature cases, (a) number of behavioral simulation, (b) p -factor and (c) r -factor

CONCLUSIONS

The objective of this study was to evaluate the influence of different air temperature data on snowmelt simulations using the SWAT model. We used spatial interpolation methods (IDW and IDWEle) combined with observed data and a statistical method with MODIS land surface temperature data (LST-Linear) to create dense air temperature data. Verification of the three different datasets at observation stations indicated that all methods can generate relatively reasonable estimates for both daily maximum and minimum air temperature. The results of runoff simulations and uncertainty analysis suggested that LST data can drive snowmelt processes of the SWAT model better than other data.

The results also indicate that the spatial distribution of the air temperature data has a strong influence on simulations,

while the observed data and the data generated by spatial interpolation can introduce uncertainties in the snowmelt model. The results suggest that MODIS land surface temperature might be a promising data source for air temperature prediction, and may expand the applicability of the SWAT model in snowmelt-dominated areas.

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SUPPLEMENTS

Text S1. Snowmelt simulation module of SWAT model

Text S2. Definition of IDWEle method

Text S3. Definition of LST-Linear method

Text S4. Calculation method of p -factor and r -factor

Figure S1. The geo-information of the test basin, (a) geo-information of observation stations, and (b) geo-information of test basin and estimation points

Figure S2. Regression analysis between daily average air temperature and elevation of interpolation stations used for IDW and IDWEle methods, (a) daily maximum air temperature, and (b) daily minimum air temperature

Table SI. Geo-information of observation stations used for IDW and IDWEle methods

Table SII. Calibration parameters of SWAT model snowmelt in the test basin

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