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Long-wave Radiation Algorithms Evaluation for Washington State

Abstract

This project evaluates the accuracy of 8 algorithms for predicting incident atmospheric long-wave radiation under clear skies, 4 cloud correction algorithms using data from Snoqualmie Pass, Washington. Clear-sky algorithms that excelled in predicting long-wave radiation were Kedding and Angstrom algorithms. Root Mean Square Deviation (RMSD) between predicted and observed 30-minute long-wave radiation averaged approximately 35 W m^{-2}. Cloud-correction algorithms of Sugita and Brutsaert represented the data best when combined with Angstrom and Garratt. Based on the results, the recommended algorithms can be applied with reasonable accuracy for predicting long-wave radiation in Snoqualmie Pass, Washington.

Introduction

Long-wave radiation is one of the key uncertainties in snowmelt modeling. Snowmelt modeling rates depend on the energy balance, and long-wave radiation contributes significantly to energy balance estimations in modeling; 80% of the energy balance is derived from shortwave and long-wave radiation. Differences between modeled and observed long-wave radiation can cause excesses of up to 200% in snowmelt modeling. This study will compare modeled results using several algorithms that were evaluated by Flerchinger et al. (2009) to observed long-wave radiation values from Snoqualmie Pass, Washington.

In energy balance estimates, shortwave radiation is dominant but long-wave radiation can provide similar amounts of energy to snowmelt processes during low solar elevations. Long-wave radiation is controlled by temperature and emissivity. Features like clouds, forest canopies, and atmospheric water vapor content levels cause emissivity to increase (Granger and Gray 1990). Atmospheric gas content greatly increases emissivity. With the impending uncertainties of global climate change and the increase of atmospheric gas content, effectively modeling the radiation budget is critical to managing the effects of changing snowmelt rates on global water resources.

Radiative transfer models have been developed for long-wave radiation (LW) estimates, but they require complex measurements of the air column above the earth's surface (Flerchinger 2009). In lieu of these expensive and complicated measurements, algorithms are widely relied on to estimate LW values. LW algorithms involve several parameters- temperature, atmospheric humidity, cloud cover, pressure, and irradiance produced by the spatial variability of topographic emissions. There has been little research conducted evaluating the efficiency of long-wave predicting algorithms. One of the largest uncertainties in long-wave modeling is successfully adjusting algorithm parameters to account for flux in weather and solar conditions.

A paper by Flerchinger (2009) summarized and evaluated 13 algorithms for predicting incident long-wave radiation under clear skies, ten cloud correction algorithms, and four algorithms for all-sky conditions. Crawford (1998) presented an improved parameterization for estimating effective atmospheric emissivity for use in calculating downwelling long-wave radiation based on temperature, humidity, pressure, and solar radiation observations. Our project investigated 8 of these algorithms summarized by Flerchinger, corrected them for cloud cover, compared them to observed LW values, and evaluated which of them is the most appropriate to use in Washington State.

Methods

Our data set was acquired through the University of Washington Snow Hydrology group. The data was from a two week period, 12:30 a.m. on 2/1/13 to 11:30 p.m. on 2/16/13, and contained temperature, relative humidity percentages, observed LW, and shortwave radiation measurements. The study had several different steps, which are broken up numerically below. Long-wave radiation is generally characterized by the formula:

$$\mathbf{L_d = \varepsilon_{eff}\sigma T^4_{eff}}$$

Where ε_{ef} represents the clear sky emissivity, σ is the Stefan Boltzmann constant, and T^4_{eff} is the near surface air temperature in Kelvin. Clear sky emissivity is the changing variable in most of the algorithms.

1) As stated above, we chose 8 algorithms from the Flerchinger paper, listed in Table 1 below, and ran the algorithms for estimated long-wave measurements. The RMSD was calculated to evaluate the success of the algorithms. The modeled results were compared with observed LW from our data set. These results were compared to the results of the Flerchinger paper.

Table 1 Clear Sky Algorithms

Angstrom (1918)	ε_{clr}=(0.83-0.18 x $10^{-0.067eo}$)
Brunt (1932)	ε_{clr}=(0.52+0.205$\sqrt{e_o}$)
Brutsaert (1975)	ε_{clr}=1.723$(e_o/T_o)^{1/7}$
Garratt (1992)	ε_{clr}=0.79-0.17exp(-0.96e_o)
Idso and Jackson (1969)	ε_{clr}=1-0.261exp(-0.00077)$(T_o$-273.16$)^2$)
Keding (1989)	ε_{clr}=0.92-0.7 x $10^{-1.2e}$
Satterlund (1979)	ε_{clr}=1.08[1-exp(-$(10_{eo})^{To/2016}$)]
Swinback (1963)	ε_{clr}=5.31 x $10^{-13}T_o^{6}$

ε_{clr} : clear sky emissivity e_o : vapor pressure T_o : temperature

2) We used 6 cloud cover correction algorithms and compiled the results for the combinations. The cloud cover corrections adjust for the fraction of cloud cover to compute effective atmospheric emissivity. Cloudiness is then estimated from the clearness index. The clearness index is the ratio of solar radiation flux density to the total hemispherical solar radiation flux density that is incident on the horizontal atmosphere surface. The cloud cover corrections are listed below in Table 2.

Table 2 Cloud cover corrections

Brutsaert (1982)	ε_a =(1+0.22c) ε_{clr}
Jacobs (1978)	ε_a=(1+0.26c) ε_{clr}
Kedding (1998)	ε_a=(1+0.153$c^{2.183}$) ε_{clr}
Maykut and Church (1973)	ε_a=(1+0.22$c^{2.75}$) ε_{clr}
Sugita and Brutsaert (1993)	ε_a=(1+0.0496$c^{2.45}$) ε_{clr}
Unsworth and Monteith (1975)	ε_a =(1-0.84c) ε_{clr} +0.84c

ε_a *:* effective atmospheric emissivity, c : fraction of cloud cover, and ε_{clr} *:* clear sky emissivity.

3) Campbell suggests that c, the cloud cover fraction, can be linearly interpolated between c = 1.0 at a clearness index (k) of 0.4 for complete cloud cover (kcld) to c = 0.0 at a clearness index of 0.7 for clear sky condition (kclr). Others have used values of 0.35

and 0.6 for kcld and kclr. We first used 0.4 and 0.7 for kcld and kclr.

Results

1) The results for the modeled long-wave estimation for the clear sky algorithms are shown below in Figure 1.

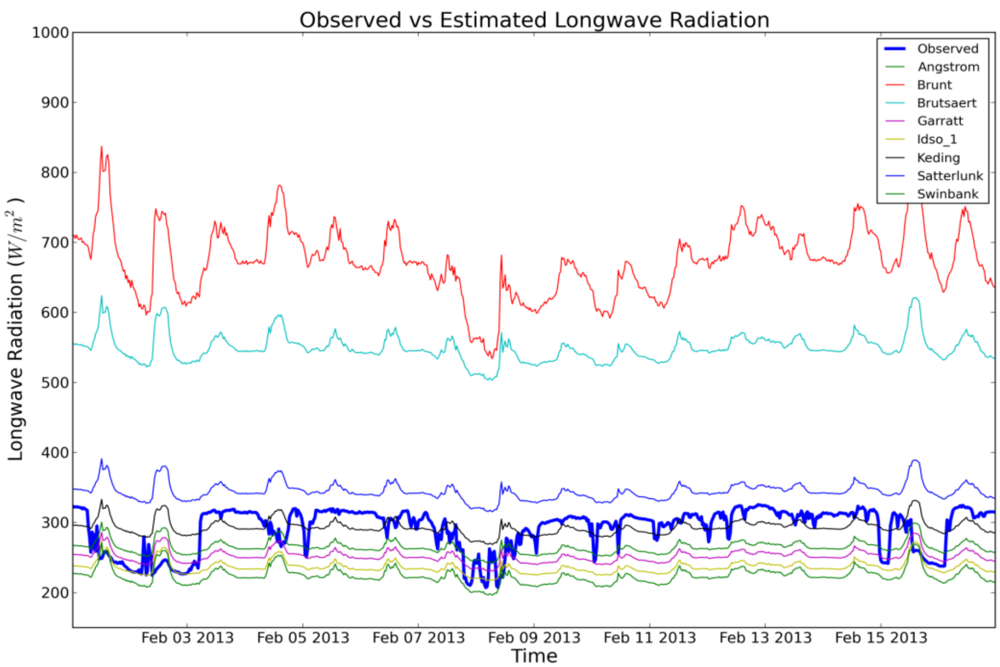

Figure 1 Long-wave radiation measurements for clear sky algorithms, modeled and observed.

Flerchinger (2009) used the root mean square deviation to look at the success of the algorithms. We calculated the RMSD and the results are listed below in Table 3.

Table 3 Root mean square deviation for clear sky algorithms

Algorithms	**RMSD**
Angstrom	40.170043
Brunt	385.569664
Brutsaert	260.328846
Garratt	49.481140
Idso_1	62.987340
Keding	30.421317
Satterlunk	61.429849
Swinbank	73.825958

2) We corrected the results for cloud cover, and compiled the RMSD. The results are shown below in Table 4.

Table 4 RMSD for cloud cover corrections

	Brutsaert	Jacobs	Kedding	Maykut	Sugita	Unsworth
Angstrom	**98.943836**	119.893333	183.623945	453.772008	**64.976228**	483.680063
Brunt	684.087218	739.124988	916.214327	1619.44339	593.175772	813.871848
Brutsaert	496.850724	540.834938	685.289296	1256.97015	424.053505	708.094630
Garratt	**88.726012**	108.280043	163.380358	419.789938	**53.475748**	474.823551
Idso_1	**80.171439**	97.303511	138.437288	377.183148	**42.577852**	463.629843
Keding	129.766744	153.037647	230.558128	531.152680	95.661853	504.139574
Satterlunk	196.701044	223.620669	316.876492	671.042634	156.347910	542.034096
Swinbank	**75.132154**	89.737616	117.758261	341.664227	**37.076821**	454.118550

3) From Table 4, we can see that the combinations between clear-sky algorithms of Angstrom, Brunt, Garratt, Swinbank and cloud correction algorithms of Brutsaert, Sugita would produce the least RMSD among all the combinations. Values for kcld and kclr in Campbell's cloud-estimation approach were evaluated for all combinations of these four clear-sky algorithms and two cloud corrections.

Table 5 gives the RMSD of Angstrom-Sugita combined algorithm with various values of kcld and kclr. The best combination for clear skies and complete cloud cover was kcld =0 and kclr = 0.7.

The best combination of kcld and kclr for the four best clear-sky algorithms and the two best cloud corrections that use cloud cover c are presented in Table 6 based on analysis similar to that in Table 5.

RMSD for combinations of the best clear-sky algorithms and cloud corrections using the values for kcld and kclr in Table 6 are given in Table 7.

Table 5 Influences of the Assumed Values of Clearness Index for Complete Cloud Cover (kcld) and Clear Skies (kclr) on RMSD of Estimated Atmospheric Long-Wave Radiation of All-Sky Conditions

	Kcld									
Kclr	**0**	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**
0.55	31.3	31.8	32.1	32.1	32.4	32.5	32.8	32.8	32.9	33.0
0.6	30.2	30.7	31.1	31.2	31.6	31.7	32.0	32.1	32.2	32.3
0.65	28.9	29.6	30.0	30.2	30.6	30.8	31.2	31.3	31.5	31.6
0.7	**27.8**	28.5	29.0	29.2	29.6	29.9	30.3	30.5	30.7	30.9
0.75	28.5	28.4	28.5	28.5	28.9	29.1	29.5	29.7	29.9	30.1
0.8	34.8	31.5	29.9	29.0	28.8	28.8	29.0	29.1	29.3	29.4
0.85	54.6	42.7	36.3	32.6	30.8	29.8	29.4	29.1	29.0	29.1
0.9	103.3	70.2	52.8	42.9	37.2	33.7	31.8	30.5	29.8	29.4
0.95	228.6	132.4	88.5	65.0	51.4	43.0	37.9	34.6	32.4	31.1
1	656.0	288.8	165.6	109.4	79.3	61.5	50.4	43.2	38.4	35.2

Table 6 Optimum Values of kclr and kcld to Minimize the RMSD of Various Combinations of the Best Clear-Sky Algorithm and Cloud Corrections

Cloud Correction Algorithm	Clear sky algorithm			
	Angstrom	Garratt	Idso_1	Swinbank
		Kcld		
Sugita	0	0	0.05	0
Brutsaert	0.45	0.45	0.45	0.45
		Kclr		
Sugita	0.7	0.75	0.85	0.85
Brutsaert	0.55	0.55	0.7	0.85

Table 7 Root Mean Square Deviations in Estimated Atmospheric Long-Wave Radiation of All-Sky Algorithms Using the Optimum Values for kcld and kclr from Table 6

Cloud Correction Algorithm	Clear sky algorithm			
	Angstrom	Garratt	Idso_1	Swinbank
Sugita	27.83	30.06	33.02	33.35
Brutsaert	36.35	32.26	36.32	40.17

Discussion:

1) For the clear sky algorithms, Kedding had the lowest RMSD and was the most successful predictor. Flerchinger (2009) found the Angstrom and Prata algorithms to have the lowest RMSD, at 22.9 and 23.1, respectively. Angstrom had the second lowest RMSD values in our study. Our RMSD results were generally higher than the Flerchinger results. Figure 2, shown below, plots the Kedding results against the observed long-wave radiation results.

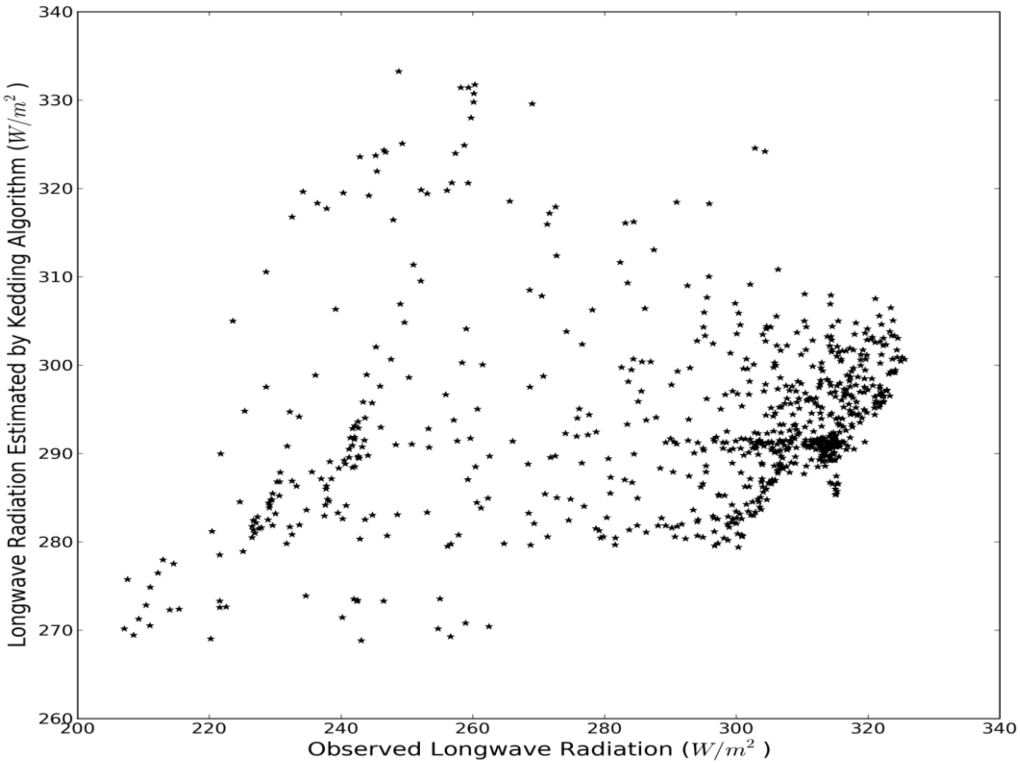

Figure 2- Kedding modeled long-wave versus observed long-wave.

There is not a linear correlation between the modeled and observed values but a defined cluster near the higher end of the estimates, which fits expectations. With a larger data set we could expect a stronger correlation.

2) The Sugita cloud correction algorithm performed the best, exhibiting the lowest RMSD value. The Sugita algorithm coupled with the Swinback, Idso_1, and the Garratt algorithm had the three lowest RMSD values. Flerchinger found that Kimball and Dilley with Angstrom and Kedding had the lowest RMSD values.

3) The least RMSD of clear-sky algorithm coms from using Kedding algorithm, which produce RMSD of 30.42, while the least cloud correction comes from the combination of Angstrom and Sugita, which yields RMSD of 27.83. Regarding RMSD, the cloud correction doesn't improve the estimation of long-wave radiation significantly.

Conclusions

The observed long-wave radiation values are within the majority of our modeled results, indicating that our modeled results provided a decent estimation. There is little difference in the RMSD values between the clear sky algorithms and cloud cover corrections. As mentioned above, our results differed significantly from the Flerchinger paper. Root mean square deviation values are calculated from observational values, which is the most likely cause of this difference. The algorithms that worked the best in our study are potentially better predictors for the climate of Washington State.

To gauge more thoroughly how well observed LW and modeled LW are correlated, a large data set needs to be analyzed. Working with a data set within a short time frame is a definite limitation of our correlation. Using observed values to evaluate the performance of the other algorithms is another limitation because it does not account for any errors or biases within the observed data. This study was most effective for determining which long-wave radiation algorithms are useful for the Washington State climate, and as a gauge for how cloud cover corrections influence results.

References

1) Class materials, data from Nicoleta Cristea, University of Washington
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3) Sicart, Jean Emmanuel, Hock, Regine, Ribstein, Pierre, Chazarin, Jean Philippe. *Sky long-wave radiation on tropical Andean glaciers: parameterization and sensitivity to atmospheric variables*. http://www.igsoc.org:8080/journal/56/199/j10j062.pdf. Accessed March 1st, 2014.