Generating reliable meteorological data in mountainous areas with scarce presence of weather records: the performance of MTCLIM in interior British Columbia, Canada

Yueh-Hsin Lo a,*, Juan A. Blanco a, Brad Seely a, Clive Welham a, James P. (Hamish) Kimmins a

aDep. Forest Sciences, University of British Columbia, 2424 Main Mall, Vancouver, B.C., V6T1Z4, Canada.
E-mails: yhlo@seed.net.tw, juan.blanco@ubc.ca, brad.seely@ubc.ca, clive.welham@ubc.ca, hamish.kimmins@ubc.ca

Research Highlights:

- We tested the weather extrapolator MTCLIM for three sites in an arid region.
- We provided a detailed validation of MTCLIM with statistical and graphical analysis.
- MTCLIM acceptably extrapolates temperatures even from short weather data series.

* Corresponding author, current address:
School of Forestry and Resource Conservation, National Taiwan University
No. 1, Sec. 4, Roosevelt Road, Taipei, 10617, Taiwan (R.O.C.)
Telephone: +886-2-3366-4638
Fax: +886-2-2363-9247
E-mail: yhlo@seed.net.tw
• MTCLIM performance for precipitation is acceptable only for monthly values.
• MTCLIM creates acceptable weather records if high daily accuracy is not needed.
Abstract

Climate models have an important role in biometeorological research in mountainous areas where few, dispersed and relatively short data records are the norm. Weather-extrapolator models are a possible solution and we tested the performance of the mountain microclimate simulation model (MTCLIM, a meteorological point data extrapolator) in three arid sites in southern interior British Columbia, representing a gradient of available meteorological information. Measures of several goodness-of-fit indices (Pearson’s correlation coefficient, coefficient of determination, mean error, mean absolute error, modeling efficiency and Theil’s inequality coefficient) and equivalence tests showed that MTCLIM simulated temperature better than precipitation and performed inside the accuracy requirements for our dendrochronological studies for both variables even with short data series. Histograms showed that predicted daily Tmax and Tmin in this arid area had some seasonal biases, probably influenced by the presence of a large water body nearby. In long-term ecological and dendrochronological studies, temporal changes of climate variables at monthly or yearly scales are usually more important than their absolute values at daily scale, and in the present study the histograms of observed and data simulated by MTCLIM at those scales were similar. Therefore, we conclude that MTCLIM can extrapolate reliable weather data for use in ecological studies in arid mountainous terrain, provided there is an adequate weather record at the reference station and proper information to calculate the input parameters: lapse rates and precipitation isohyets.

Keywords: climate model; MTCLIM; model validation; climate downscaling; weather data extrapolation; forest climate
Software availability

Name of the software: MounTain microCLIMate simulation model (MTCLIM) v4.3.
Developer: Steve W. Running
Contact info: Numerical Terradynamic Simulation Group (NTSG), College of Forestry & Conservation, The University of Montana, 32 Campus Drive, Missoula, MT 59812. Phone +1 406 243 6311, Fax: +1 406 243 4510, E-mail swr@ntsg.umt.edu
Year first available: 1987
Hardware required: PC, 128Mb RAM or higher
Software required: Windows 98 or higher
Program language: Microsoft Excel / C++
Program Size: Excel version: 345 Kb; C++ version: 118 Kb
Availability and Cost: Downloadable for free from http://www.ntsg.umt.edu/models/bgc/

1. Introduction

A complete and accurate source of weather data is a prerequisite for the efficient modeling of a wide variety of environmental processes (Jeffrey et al., 2001). As hydrological and ecological research on the potential impacts of climate change on ecosystems and ecological processes continues developing, there is an increasing demand for reliable meteorological data (Thornton et al., 1997; Thornton and Running, 1999; Hamann and Wang, 2005; McKeeny et al., 2006). Dendroclimatological research that studies the relationships between climate variability and annual tree growth is becoming increasingly popular (Lo et al., 2010 a, b). However, due to the cost of building and maintaining comprehensive networks of long-term weather monitoring installations (Glassy and Running, 1994), there rarely are sufficient weather data records for some regions, especially in areas with mountainous topography. In many applications, the success or at least accuracy of point simulations can be critically dependent upon the
availability of observational data within an acceptable distance of the location under investigation. Due to the scarcity of observational networks in mountainous and low-populated areas, the distance to the nearest station can be large (Jeffrey et al., 2001), and the point of interest is usually situated not only far but also at a different altitude from the nearest weather station. As a consequence, when climate data are needed as inputs to run ecosystem models or dendroclimatological research in such areas, it is often necessary to use data extrapolated from the nearest weather station (Thornton et al., 1997; McKeeny et al., 2006).

In general, as elevation increases, temperature decreases, with a widely used average annual temperature/elevation lapse rate of 6.4 °C per 1000 m (Dodson and Marks, 1997; Lookinbill and Urban, 2003). Precipitation generally reflects an equivalent lapse rate, with more rain and snow at higher than at lower elevations. However, topography, slope, aspect, land cover and other local factors can have a strong influence on these simple relationships (Barry and Chorley, 1998). Statistical methods developed to extrapolate climate variables include inverse-distance methods or optimal interpolation procedures such as kriging or smoothing splines (Custer et al., 1996; Thornton et al., 1997; Hamann and Wang, 2005). These methods are easy to calculate and results are quite reliable if the target area has similar topography to that of the reference area and there are several weather stations that can be cross-referenced (Thornton et al., 1997; McKeeny et al., 2006). However, one common drawback is that in many situations topography is complex and there are few weather stations, and unbalanced distributions of sample stations can be problematic (Hamann and Wang, 2005). Without considering local factors these calculations could fail to generate reliable climate data for those areas where the topography is complicated (Custer et al., 1996; Almeida and Landsberg, 2003).

Several climate models have been developed for this purpose. Two models widely used in North America are the parameter-elevation regressions on independent slopes model (PRISM, Daly et al., 2008), and DAYMET (Thornton et al., 1997). They are spatial interpolation/extrapolation systems that create a continuous climate data grid based on multiple weather stations. Another model is the mountain microclimate simulation model (MTCLIM, Running et al., 1987), which extrapolates the data from a single weather station to a single target point. Some examples of their use can be found in Glassy and
Running (1994), Thornton et al. (1997), Almeida and Landsberg (2003), Hunter and Meentemeyer (2005), among others. The model Australian National University spline routine (ANUSPLIN, Hutchinson and Bischof, 1983), originally developed in Australia, has also been applied in North America (Custer et al., 1996; McKeeny et al., 2006). Finally, there is also a local model for British Columbia, the McGregor model forest climate model (MFCLiM), a GIS-based monthly climate model (Benton, 1997).

In order to use those climate models as decision-support tools for natural resource policy and management and for dendroclimatological research, their predictions must be reliable, especially in areas of high latitude or elevation, where it is expected that climate change will be more critical. However, these zones usually have the lowest number of available climate records, and they are usually very disperse, short or incomplete. In addition, weather generators usually underperform in arid and semi-arid conditions (Döll et al., 2003), where phenomena hard to simulated such as mist, frost, dew and fog can became an important proportion of water inputs into the system. As a consequence, the correct use of weather models in environmental studies for these regions is critical, and therefore the reliability of their projections must be rigorously tested.

The appropriateness of different methods for model validation has engendered considerable discussion (Gardner and Urban, 2003), but there is general agreement that model predictions should be tested against independent data (Blanco et al., 2007). Model validation is an exercise to show that predictions are close enough to independent empirical data to make them useful for specific and practical applications, and that decisions based on model output are defensible (Oreskes et al., 1994; Rykiel, 1996). Recognizing the importance of model evaluation, *Environmental Modelling & Software* has a strong focus on validation (Jakeman et al., 2006), which has been identified as a crucial step when developing and implementing new environmental models (e.g. Robson et al., 2008; Welsh, 2008).

In this context, MTCLIM has been applied as a stand-alone model in several countries (Almeida and Landsberg, 2003, and references above), or linked with other models to provide single-point meteorological input (Venevsky and Maksytunov, 2007; Sheng et al., 2009). MTCLIM’s logic has been tested for temperate areas by Glassy and Running (1994), who found an acceptable model performance.
but recommended some improvements. In addition, Kimball et al. (1997) and Thornton and Running (1999) tested MTCLIM’s algorithms to calculate air humidity and solar radiation in arid sites. However, MTCLIM performance to extrapolate air temperature and precipitation under semi-arid conditions where accurate estimations of precipitation are especially important has not been tested yet. In addition, MTCLIM performance under different quality and length of weather records used as input also needs to be assessed. In order to fill this gap, the objective of this paper is to test MTCLIM estimates for three different mountain sites with different levels of weather record length and closeness to the nearest weather station. These three sites are placed in the Okanagan Valley, a semi-arid region in the southern interior of British Columbia, Canada. This test of MTCLIM performance was part of our dendroclimatological research in the area, in which we explored the relationships between tree growth and climate variability (see Lo et al., 2010b, for a detailed description of the dendrochronological side of our work).

2. Material and methods

2.1. Model description

MTCLIM (MounTain microCLIMate simulation model) has been presented by Running et al. (1987) and therefore only a basic description is provided here. MTCLIM is a model which generates daily weather data for a target area extrapolating daily data from a reference weather station. Input variables include daily maximum and minimum temperature and precipitation data, and geographic information for the reference and target location (i.e. elevation, slope, aspect, and latitude). Temperature and moisture regimes are extrapolated on the basis of lapse rate and precipitation isohyets, respectively (Thornton et al., 1997). Based on the input data the model produces daily maximum and minimum temperatures, daily mean temperature, daily precipitation, vapor pressure deficit, daily solar radiation and day length (Coughlan and Running, 1997; Kimball et al., 1997; Thornton and Running, 1999; Chiesi et al., 2002). In this paper we test MTCLIM performance for maximum and minimum temperatures and precipitation extrapolations, which in MTCLIM depend entirely on the user-defined lapse rates and isohyets. Values of
daily vapor pressure deficit, solar radiation and day length were also calculated but not included in this paper.

Maximum and minimum temperatures for the target point \((T_{\text{MAX target}}, T_{\text{MIN target}})\) are calculated as follows:

\[
T_{\text{MAX target}} = T_{\text{MAX reference}} + \left( \Delta \text{Elevation} \times T_{\text{MAX lapse rate}} \right)
\]

\[
T_{\text{MIN target}} = T_{\text{MIN reference}} + \left( \Delta \text{Elevation} \times T_{\text{MIN lapse rate}} \right)
\]  

(1)

Where \(T_{\text{MAX reference}}\) and \(T_{\text{MIN reference}}\) are the daily maximum and minimum temperatures in the reference station, \(\Delta \text{Elevation}\) is the difference in elevation between the reference station and the target point and \(T_{\text{MAX lapse rate}}\) and \(T_{\text{MIN lapse rate}}\) are the user-defined lapse rates for the maximum and minimum temperatures.

MTCLIM estimates the mean daily temperature of the target point \((T_{\text{DAY target}})\) as indicated below:

\[
T_{\text{DAY target}} = 0.45 \times \left( T_{\text{MAX target}} - T_{\text{AVG target}} \right) + T_{\text{AVG target}}
\]  

(2)

where \(T_{\text{AVG target}}\) is the arithmetic average of \(T_{\text{MAX target}}\) and \(T_{\text{MIN target}}\). However, we did not evaluate MTCLIM’s performance for this value as it is derived from \(T_{\text{MAX target}}\) and \(T_{\text{MIN target}}\).

Precipitation in the target point \((P_{\text{target}})\) is calculated as follows:

\[
P_{\text{target}} = P_{\text{reference}} \times \frac{P_{\text{target isohyet}}}{P_{\text{reference isohyet}}}
\]  

(3)

where \(P_{\text{reference}}\) is the daily precipitation at the reference station and \(P_{\text{target isohyet}}\) and \(P_{\text{reference isohyet}}\) are the user-defined annual precipitation isohyets for the target site and reference station, respectively.

2.2. Model calibration

To calculate the lapse rates for the maximum and minimum temperatures, we used the average monthly data from Environment Canada’s network of 14 weather stations in the region and plotted them against the elevation. The regressions obtained were:

\[
\text{Monthly } T_{\text{MAX}} (\degree \text{C}) = -0.006 \text{ Elevation (m)} + 16.246 \quad R^2 = 0.874 \]  

(4)

\[
\text{Monthly } T_{\text{MIN}} (\degree \text{C}) = -0.004 \text{ Elevation (m)} + 4.011 \quad R^2 = 0.762
\]  

(5)
From these regressions, the values of $T_{\text{MAX lapse rate}}$ and $T_{\text{MIN lapse rate}}$ were defined as 6 °C 1000m$^{-1}$ and 4 °C 1000m$^{-1}$, respectively. Similarly, values of annual precipitation were plotted against elevation, being the best fit the following curve:

$$\text{Annual P (mm)} = 0.0003 \text{Elevation}^2(m)-0.3223 \text{Elevation (m)} + 458.98 \quad R^2 = 0.824 \quad (6)$$

The annual isohyets for each target site were calculated by inputting their corresponding elevations in the previous equation (Table 1), whereas the base isohyet for each reference site was calculated as the average annual precipitation for the available data series (Table 2). More details about this methodology can be found in Lo (2009).

2.3. Methodology to test the performance of MTCLIM in the study area

We tested the estimates from MTCLIM using three pairs of weather stations in the Okanagan Valley, Kamloops forest region, southern interior of B.C. Data defining the locations are listed in Table 1 and Figure 1, with a summary of climate averages for the area provided in Table 2. These stations were selected because each pair included both high and low elevation climate records. In each pair, the climate record from the low elevation site (the reference site) was the input data for MTCLIM and the climate record from the high elevation site (the target site) was compared against MTCLIM simulations for the high elevation climate. These pairs were: Pair 1: Hedley vs. Hedley Mine; Pair 2: Vernon vs. Silver Star; and Pair 3: McCulloch vs. Big White. Pair 1 represented the ideal situation of long-term climate data and the reference station close to the target site. Pair 2 is an example of new automatic weather stations, with short climate record but close to the target site. Pair 3 represents the common situation in many mountainous areas around the world with relatively short presence of weather stations and far from the target site. All stations were located in the southern very dry zone of the Kamloops forest region as defined by Lloyd et al. (1990). The evaluation process was carried out in three steps.

First, MTCLIM requires the reference station to have no missing values within any given year or the algorithm stops. Missing days were usually grouped as whole months missing from the reference station (i.e. Hedley, Vernon and McCulloch). Those months were removed from the records. In the few other
cases, if the cluster of missing days was 3 days or less we estimated the weather variables values by interpolation between the previous and following days to fill the gap. If the gap was 4 to 15 days wide we estimated the values as the average of the month, and if more than 15 days were missing we removed the whole month from the dataset.

Second, we used MTCLIM to generate values for daily maximum, minimum and mean temperatures, daily precipitation, vapor pressure deficit, solar radiation and day length for each of the corresponding high elevation sites in each pair (Hedley Mine, Silver Star, Big White), but only results for maximum and minimum temperatures and precipitation are presented here. Annual precipitation isohyets of 783 mm, 694 mm and 885 mm were used in Hedley Mine, Silver Star and Big White, respectively (calculated with the equations described earlier in section 2.2).

Third, recorded data from the high elevation sites were compared with the MTCLIM estimates for the same sites using frequency histograms, regression analysis and goodness-of-fit indices. These indices were: Pearson’s correlation coefficient ($r$), coefficient of determination ($r^2$), mean error (MER), mean absolute error (MAE), modeling efficiency (ME) and Theil’s inequality coefficient (U). Mean error (MER) was calculated to identify the overall directionality of the bias:

$$MER = \frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)$$

(7)

where $n$ is the number of pairs, $P_i$ is the $i^{th}$ predicted value and $O_i$ is the $i^{th}$ observed value. Positive and negative MER values indicate over- and under-estimate, respectively. Mean absolute error (MAE) was computed to determine overall magnitude of error:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |(P_i - O_i)|$$

(8)

Modeling efficiency was calculated as defined by Vanclay and Skovsgaard (1997) as:

$$ME = 1 - \frac{\sum_{i=1}^{n} D_i^2}{\sum_{i=1}^{n} (O_i - \bar{P}_i)^2}$$

(9)
where $D_i = O_i - P_i$. This statistic provides a simple index of performance on a relative scale, where $ME = 1$ indicates a perfect fit, $ME = 0$ indicates that the model is no better than a simple average of the estimated values, while negative values indicate poor model performance. Theil’s inequality coefficient (Theil, 1966) was calculated as:

$$U = \sqrt{\frac{\sum_{i=1}^{n} D_i^2}{\sum_{i=1}^{n} O_i^2}}$$

(10)

$U$ can assume values of 0 and greater. If $U < 1$ then the model produces better estimates than assuming the variable is constant and it does not change, with $U = 0$ indicating perfect estimates. If $U = 1$ the model produces estimates that are not better than assuming the variable does not change, and if $U > 1$ the predictive power of the model is worse than not using a model and keeping the no-change assumption.

Finally, we evaluated the null hypothesis of dissimilarity between the populations of observed and predicted values using equivalence tests. This test requires the user to select a criterion to define the acceptable level of model accuracy (Robinson and Froese, 2004). Our criteria to accept model performance for our posterior dendroclimatological work were: 1) model extrapolations should be biased less than 1.5°C or 40% for precipitation, and 2) the absolute values of the mean bias should be less than 25% or 50% of the standard deviation of recorded values ($\varepsilon = 0.25$ or 0.50 for ‘strict’ and ‘liberal’ tests, respectively, following the guidelines by Welleck, 2003). We compared the $t$-value calculated as:

$$t_d = \frac{\bar{X}_{\text{observed}}}{S_{\bar{X}_{\text{observed}}}}$$

(11)

If the $t$-value was lower than the cutoff, the null hypothesis of dissimilarity was rejected (Robinson and Froese, 2004), with the cutoff being the $\alpha$-quantile of the non-central $F$ distribution with degrees of freedom $\nu_1 = 1$ and $\nu_2 = n - 1$, and non-centrality parameter $\psi^2 = n \times \varepsilon^2$. In essence, the test is to check whether the critical values (at $\alpha = 0.05$) of a two-tailed $F$ distribution (the cutoff) are contained within the rejection region defined by the selected criteria ($-\varepsilon$, $+\varepsilon$). The power of this test was calculated using the
following equation (Wellek, 2003):

$$\text{Power}_{\alpha, n-1} (\varepsilon) = 2F_t (Cutoff_{\alpha, n-1} (\varepsilon)) - 1$$  \hspace{1cm} (12)

where \(F_t\) is the cumulative distribution function for the non-central \(t\) distribution.

3. Results

Tables 3 to 5 present indices of model performance for monthly maximum and maximum temperatures and monthly total precipitation for the three target sites (Hedley Mine, Silver Star and Big White). Pearson’s correlation coefficients between the observed data and the simulated data for maximum and minimum temperatures at all three sites had high values \((r > 0.90\) for monthly values and \(r > 0.68\) for daily values, Tables 3 and 4\). For precipitation, \(r\) values were also high for the Pair 1, but just moderate for Pairs 2 and 3 (Table 5).

The coefficients of determination \((r^2)\) were also high for both maximum and minimum temperature for Pairs 1 and 2, but with slightly lower values for Pair 3 (Big White, Tables 3 and 4 and scatterplots in additional supporting material). For precipitation, the variance explained by the model was high for Pair 1 but low for Pairs 2 and 3 (Table 5). \(M\)ER for maximum temperature ranged from -0.16 to 0.50 °C for monthly values and -0.78 to 2.55 °C for daily values. For minimum temperatures, \(M\)ER ranged from -0.23 to 3.15 °C for monthly values and -2.85 to -0.81 °C for monthly values. As for precipitation, \(M\)ER was always larger for monthly values as it refers to the accumulated value (and not the average as for temperature). Monthly \(M\)ER values amounted to about 1 to 2 % of annual total precipitation. MAE showed that model output had higher variation for predicted maximum than for predicted minimum temperature with the exception of minimum temperature at Big White (Tables 3 and 4). MAE for precipitation ranged from 11.91 to 24.57 mm for monthly values (Table 5).

Both model efficiency and Theil’s \(U\) index showed that MTCLIM performed well for temperature, indicating clear gains by using the model compared to the use of long-term average values (not using a
model) from the reference station (Tables 3 and 4). Similarly, for precipitation indices, the model performed well as measured by the indices at monthly scale at the three Pairs and daily scale for Pair 1 and 2, even though there were some biases. Predicted annual precipitation values were systematically lower than the instrumental records (Table 5).

Figures 2 to 4 compared monthly frequency histograms of observed and predicted $T_{\text{MAX}}$ and $T_{\text{MIN}}$ and monthly precipitation at Hedley Mine. The distributions of observed and simulated data were similar for both $T_{\text{MAX}}$ and $T_{\text{MIN}}$ (Figures 5 and 6), but the means were different and there was a tendency to have more dispersion in the distribution of observed values than in the simulated ones. The Q-Q plots for precipitation were less similar to the 1:1 line (Figure 7), indicating a higher dispersion and skewness in the observed precipitation data. Similar results were obtained for Silver Star (see additional supporting material), but at Big White, the differences between observed and simulated distributions for precipitations were greater (Figures 8 and 9).

MTCLIM estimates of average monthly $T_{\text{MAX}}$ showed seasonal variations. In fall-winter, model estimates were lower than the monthly average of recorded data (a seasonal average of -2.58°C in Big White, -2.64°C in Hedley Mine and -0.20°C in Silver Star). However, in spring-summer the average of simulated values were higher than the average of recorded data (a seasonal average of 1.52°C in Big White, 1.86°C in Hedley Mine and 2.89°C in Silver Star). Monthly averages of predicted $T_{\text{MIN}}$ were systematically lower than recorded values through the year in Big White and Silver Star, and also most of the year (except in January, April and October) in Hedley Mine.

Significant positive linear relationships between the simulated and observed $T_{\text{MAX}}$ and $T_{\text{MIN}}$ were obtained for Hedley Mine and Silver Star (see additional material), although for $T_{\text{MAX}}$, the highest $r^2$ occurred in the summer, while for $T_{\text{MIN}}$ the highest $r^2$ occurred in winter. For precipitation (Figures 3 and 6), the highest $r^2$ occurred in summer at Hedley but no pattern was found at Silver Star. For Big White, the regression results in Figure 7 show that MTCLIM was successful at simulating temperature with high $r^2$ but not for precipitation. It did well at simulating results in some months (e.g. March and December).
while for other months it simulated poorly (e.g. February and April).

Finally, equivalence tests indicated that the dissimilarity between distributions can be rejected for both $T_{\text{MAX}}$ and $T_{\text{MIN}}$ in the three sites for daily values, but for monthly values this hypothesis cannot be rejected for Big White even under a relaxed accuracy need. As for the distribution of precipitation monthly values, dissimilarity is rejected only for Hedley Mine with a relaxed need of accuracy (Table 6).

4. Discussion

4.1. Model performance for temperature

The ability of MTCLIM to simulate temperature in the central Okanagan Valley was generally acceptable. When the results were analyzed in a monthly time scale, the model produced very high correlation coefficients, indicating that a high proportion of the variance was captured by MTCLIM. Compared to previous applications of MTCLIM in other areas (Almeida and Landsberg, 2003), the $r^2$ values presented here are higher and the biases for monthly temperatures are relatively small (Benton, 1997; Hamann and Wang, 2005; McKeeny et al., 2006). However, as the distance between the base weather station and the target site increased so did the bias, though it was still within acceptable limits as defined by other detailed climatological studies in this region (1.5°C or less for temperature and 40% for precipitation; Dodson and Marks, 1997; McKeeny et al., 2006). Two other indices of model performance also indicated that model’s estimates were acceptable. All modeling efficiency values for monthly data were above 0.86 and Theil’s $U$ indices were close to zero, with the exception of $T_{\text{MIN}}$ at Big White. This clearly indicates that MTCLIM’s estimates were better when weather stations were closer geographically and when longer data series were used, a result certainly not surprising. Even for $T_{\text{MIN}}$ at Big White, the indices were lower but still indicated acceptable model performance as defined by our criteria.

In addition, the histograms of daily values and their standard deviations were similar, although with slightly different means. Among the three data sites, both Hedley Mine and Silver Star had similar monthly histograms for observed and predicted distributions. As the length of the available weather
records at the reference station increased (i.e. Hedley Mine vs. Big White), the shapes of the histograms of daily temperature values became more similar. We can also expect that, commonly to other climate-generation models that produce more accurate predictions when more information is used (McKeeny et al., 2006), the accuracy of MTCLIM extrapolating temperature and precipitation will increase with the increase in the length of the weather records used to estimate the lapse rates and isohyets. In addition, the longer is the time simulated, the more similar the simulated and recorded average values would be (as the possible under- and overestimated daily values could cancel each other) and therefore the average model performance would be better.

MTCLIM also performed reasonably well (as defined by our criteria for dendroclimatological research) at predicting climate on a monthly time scale. Monthly data are important in broad-scale ecological studies because tree and plant growth responds closely to monthly temperature and precipitation values during average weather conditions (Lo, 2009; Lo et al., 2010a). This is especially important in our dendroclimatological research, where accumulated tree growth was related to monthly values of temperature and precipitation and other derived variables, such as accumulated degree-days or monthly evapotranspiration (Lo et al., 2010b). Because tree growth occurs only during the growing season when air temperature is above ~5°C, in our case the correct estimation of minimum temperatures during the summer was the most important requirement. If the model underperformed during the winter we considered it was not an issue as during this time the biological activity of trees is much reduced. However, some daily extreme weather events like frost or heat waves can also affect tree growth. The distribution of predicted daily values for each month was very similar to the climate records, although some systematic bias was evident for $T_{MAX}$ in winter (predicted values lower than observed) and summer (predicted values higher than observed).

One possible reason is that these weather stations are close to the Okanagan Lake system (432 km$^2$ of water bodies), and lakes usually have a buffering effect on temperature due to their capacity to store latent heat. Lakes release heat in the winter making air warmer and they store heat in the summer reducing air temperature (Barry and Chorley, 1998; McKeeny et al., 2006). Another possible reason is that the lapse
rates used were not appropriate for all seasons. During winter, the change in daily maximum temperature with elevation is often smaller than in summer, and could be affected by thermal inversions. Therefore, the average lapse rate of 6 °C km\(^{-1}\) could have caused an under-estimation of temperatures, especially in Pair 2, the one directly in the main and deepest valley. During the summer, lapse rates can be quite steep, thus causing the model to over-estimate the maximum temperature. However, these issues were less important in Pair 1 (as it is separated from the main central valley by several hills) and probably negligible in Pair 3 (where both stations were in high elevation and likely above the thermal inversion layer) (Figure 1). These parameters are very important as they are the only factors affecting MTCLIM simulations (Chiesi et al., 2002). Lapse rates fluctuate at many scales (seasonally, diurnally and spatially), but the average annual lapse rates for wide regions usually approach values of 6-7 °C km\(^{-1}\) (Lowry, 1969; Dodson and Marks, 1997; Barry and Chorley, 1998). However, precipitation isohyets vary more because of large water bodies, complex terrain, rain shadow and upward and downward air mass movements, and a more accurate estimation depends on station density available in the target region (Custer et al., 1996).

4.2. Model performance for precipitation

MTCLIM did not predict precipitation as reliably as temperature. The model showed a tendency to produce lower monthly precipitation than observed in the records. This could be a concern since precipitation is a critical component of all climate models, and especially when they are applied to arid regions. This result is not surprising because rainfall patterns are more difficult to simulate as they vary more on spatial and temporal scales than temperature and they are not as strongly related to altitude as temperature is (Chiesi et al., 2002; Burton et al., 2008). In fact, simulation biases of the model were just about one to two percent (-11.25 to 9.26 mm, Table 5) of the annual average, which can be considered acceptable for our application. Although \(r^2\) values were lower than desirable, they were acceptable (except for spring values in the pairs lacking a long data record) and were higher than described in a previous MTCLIM study in a Mediterranean area (Chiesi et al., 2002). In general, the bottom of the Okanagan Valley is drier than the mountain tops (Lloyd et al., 1990). Precipitation in this area can also be markedly
affected by air mass movements and global climatic oscillations (e.g. storms, El Niño and La Niña events or the Pacific Decadal Oscillation), which are not accounted for in MTCLIM.

The lower performance for precipitation compared to temperature could also be due to the smaller sample size (shorter simulated weather records and more missing days in the reference stations). However, similarly to temperature projections, as the sample size (number of years recorded at the reference station) increased, the model performance improved for monthly values, with the histograms of extrapolated daily values for each month being more similar to the histograms of observed precipitation. However, even with careful selection of the input parameters (target and base isohyets), the bias in precipitation is still large compared to the ones for maximum and minimum temperatures, which is consistent with previous research (Thornton et al., 1997; Chiesi et al., 2002). One important distinction with those previous studies is that we carried out the analysis for a longer time scale using a small number of stations, whereas typically a larger number of stations have been used on relatively short time scales (a year or less). All things considered, the poor model performance for precipitation compared to temperature seems to be an artifact of MTCLIM that should be taken into account when using the model in new areas.

4.3. MTCLIM potential as a biometeorological research tool in arid and mountainous areas

The adequate performance of MTCLIM when predicting temperature is also a benefit for predicting air humidity because in dry regions it is important to accurately estimate minimum temperatures to calculate dew point (which is a key point to determine how much humidity is in the air, Running et al., 1987), as the lower precipitation makes air humidity more critical in arid than in humid areas (Kimball et al., 1997). As Glassy and Running (1994) pointed out “for larger scale spatial modeling applications precise meteorology may not be as important as a good general characterization of the regional climatology.” The fact that in the present study MTCLIM generated monthly histograms of climatic variables consistent with the observed records encourages us to conclude that in this area the model is a useful tool in weather- and climate-related environmental research, and it is therefore suitable for use in
other arid and mountainous areas at least at monthly time scales.

The three pairs of stations represented three different conditions of availability of climate records. The Hedley Mine pair (Pair 1) was the most ideal because it had long-term climate data and the two weather stations were close to each other. It is also located in the driest part of the Okanagan Valley, which has an increasing rainfall gradient from south to north (Lloyd et al., 1990). The Silver Star pair (Pair 2) had the shortest climate data record, but the base and target stations were close to each other, a situation that is probably representative of most of the studies in the mountainous areas of North America and parts of Europe and East Asia where automatic weather stations have recently been established in many areas where it was previously too expensive or impractical to maintain human-operated stations. The model working under such conditions performed in a very similar way to the ideal conditions of Pair 1, and therefore having short climate records should not be considered as an insurmountable handicap to use MTCLIM in a new region, provided that the base and target sites are close and the records are complete. On the other hand, the Big White pair (Pair 3) represented a relatively short climate record and the two weather stations were far apart. Big White is a ski resort that opened in 1990 in a relatively isolated area of Monashee Mountain range, and only winter records (when the resort is open) are available. Such lack of complete and long term data sets is common in many ecological studies in which the base weather station is not close to the experimental site, especially in areas with low human density, or the weather records are incomplete. However, our results suggest that even in such circumstances MTCLIM can be useful for general climate characterizations, although the actual values of the variables should be taken with caution, especially for precipitation. When applying MTCLIM to new regions a careful study of the regional climate values of temperature lapse rates and precipitation isohyets should be carried out in advance to reduce the influence of low-quality weather records to the minimum. Such study should involve calculating average lapse rates for different seasons, analyzing the evolution of daily values of lapse rates and studying the effects of thermal inversions and thermal layering of the atmosphere on lapse rates, but we recognize that this would be difficult in areas with poor records, such our Pair 3. This would be especially important if high accuracy is needed for a daily time scale.
Overall, our results show that if there is an adequate length of climate records at the reference base and proper input parameters MTCLIM can provide quite reliable weather data for use in ecological and biometeorological research or management planning in mountainous terrain in arid zones at monthly time scales. However, using synthetic weather data generated with simple point weather-extrapolators such as MTCLIM for eco-physiological studies sensitive to daily changes in temperature may not be adequate. Sensitivity analyses and estimation of parameter uncertainty and error propagation also need to be done to identify how estimates change based on the specified error and bias of input parameters (Hamann and Wang, 2005). Future research should also examine the effect on model output of combining data from several weather stations, rather than just a single station. Finally, the possibility of modifying MTCLIM to account for the influence of large water bodies should be considered, given that in its current version MTCLIM lacks the ability to capture the influences of big lakes, like the Okanagan Lake in our case (Glassy and Running, 1994; Hunter and Meentemeyer, 2005). A possible way to increase model performance in such cases could be by incorporating some lapse rates modifiers dependent on the distance to a water body of a given size and the option of using seasonal lapse rates in addition to the annual average. Model users should keep these limitations in mind and interpret model output critically.

Acknowledgements

This study is based on a research project funded by the Sustainable Forest Management Network of Canada (SFN Network ref: kimminshmode8). We thank Dr. Andy Black for his helpful comments and the three anonymous reviewers for their useful suggestions that have greatly helped to improve this paper.

References


Dodson, R., Marks, D., 1997. Daily air temperature interpolated at high spatial resolution over a large mountainous region. Climate Research 8 1-20.


Lo et al. (2011)


Figure captions

Figure 1. Map of the situation of the weather stations in the Okanagan Valley area. Reference stations are marked with open circles. Target stations are marked with open triangles and underlined font (adapted from Natural Resources Canada, 2010).

Figure 2. Monthly relative-frequency distribution histograms of daily maximum temperature comparing observed (gray areas) and simulated (areas under the black lines) data at Hedley Mine for the years given in Table 2. Solid vertical lines indicate the average value of observed records. Broken vertical lines indicate the average value of MTCLIM estimates. SD_o stands for value of standard deviation (in °C) of observed records. SD_M stands for value of standard deviation (in °C) of MTCLIM estimates and $r^2$ indicates the coefficient of determination of the linear regression observed vs. estimated, followed by a star (*) if the regression is significant at $p < 0.05$.

Figure 3. Monthly relative-frequency distribution histograms of daily minimum temperature comparing observed (gray areas) and simulated (areas under the black lines) data at Hedley Mine for the years given in Table 2. Solid vertical lines indicate the average value of observed records. Broken vertical lines indicate the average value of MTCLIM estimates. SD_o stands for value of standard deviation (in °C) of observed records. SD_M stands for value of standard deviation (in °C) of MTCLIM estimates and $r^2$ indicates the coefficient of determination of the linear regression observed vs. estimated, followed by a star (*) if the regression is significant at $p < 0.05$.

Figure 4. Monthly relative-frequency distribution histogram of accumulated monthly precipitation comparing observed (gray area) and simulated (areas under the black lines) data at Hedley Mine for the years given in Table 2. Solid vertical lines indicate the average value of observed records. Broken vertical lines indicate the average value of MTCLIM estimates. Solid vertical lines indicate the average value of
observed records. Broken vertical lines indicate the average value of MTCLIM estimates. SD\textsubscript{O} stands for value of standard deviation (in mm) of observed records. SD\textsubscript{M} stands for value of standard deviation (in mm) of MTCLIM estimates and \( r^2 \) indicates the coefficient of determination of the linear regression observed vs. estimated, followed by a star (*) if the regression is significant at p \(<\) 0.05.

Figure 5. Quantile-quantile plots for the distribution of observed and simulated data of maximum daily temperatures at Hedley Mine. r: probability plot correlation coefficient.

Figure 6. Quantile-quantile plots for the distribution of observed and simulated data of minimum daily temperatures at Hedley Mine. r: probability plot correlation coefficient.

Figure 7. Quantile-quantile plots for the distribution of observed and simulated data of monthly precipitation at Hedley Mine. r: probability plot correlation coefficient.

Figure 8. Monthly relative-frequency distribution histograms of daily maximum and minimum temperature and monthly precipitation comparing observed (gray areas) and simulated (areas under the black lines) data at Big White for the years given in Table 2. Solid vertical lines indicate the average value of observed records. Broken vertical lines indicate the average value of MTCLIM estimates. SD\textsubscript{O} stands for value of standard deviation (in °C) of observed records. SD\textsubscript{M} stands for value of standard deviation (in °C) of MTCLIM estimates and \( r^2 \) indicates the coefficient of determination of the linear regression observed vs. estimated, followed by a star (*) if the regression is significant at p \(<\) 0.05.

Figure 9. Quantile-quantile plots for the distribution of observed and simulated data of daily maximum and minimum temperatures and monthly precipitation at Big White. r: probability plot correlation coefficient.
Table 1. Geographic information for the weather stations used to test MTCLIM. Records from target stations were not used for simulation, only for model evaluation.

<table>
<thead>
<tr>
<th>Station</th>
<th>Type</th>
<th>Pair</th>
<th>Latitude N</th>
<th>Longitude W</th>
<th>Elevation (m)</th>
<th>Recorded period</th>
<th>Simulated period</th>
<th>Missing years</th>
<th>Available years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedley</td>
<td>Reference</td>
<td>1</td>
<td>49.357</td>
<td>120.077</td>
<td>517</td>
<td>1904 - 2002</td>
<td>1909 - 2001</td>
<td>33</td>
<td>59</td>
</tr>
<tr>
<td>Hedley Mine</td>
<td>Target</td>
<td>1</td>
<td>49.369</td>
<td>120.022</td>
<td>1,707</td>
<td>1904 - 2002</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Silver Star</td>
<td>Target</td>
<td>2</td>
<td>50.358</td>
<td>119.056</td>
<td>1,572</td>
<td>1971 - 2002</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>McCulloch</td>
<td>Reference</td>
<td>3</td>
<td>49.800</td>
<td>119.200</td>
<td>1,250</td>
<td>1936 - 1993</td>
<td>1971 - 1993</td>
<td>2</td>
<td>20</td>
</tr>
<tr>
<td>Big White</td>
<td>Target</td>
<td>3</td>
<td>49.733</td>
<td>118.933</td>
<td>1,841</td>
<td>1971 - 1999</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

1 First and last year simulated with MTCLIM using the reference station record.

2 Number of years removed from the reference station record prior to the simulation due to missing data (see text).

3 Number of year with full records simulated with MTCLIM.
Table 2. Monthly temperature and precipitation summary of the testing sites for the period 1970-2000 (Environment Canada, 2008). R: Reference station; T: Target Station, Corr: correlation coefficient between the reference and target station recorded values of T and P.

<table>
<thead>
<tr>
<th>Site</th>
<th>Variable</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
<th>Year</th>
<th>Corr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedley (R)</td>
<td>Daily Average (°C)</td>
<td>-4.0</td>
<td>-0.5</td>
<td>4.4</td>
<td>8.9</td>
<td>13.2</td>
<td>16.8</td>
<td>19.9</td>
<td>19.7</td>
<td>14.7</td>
<td>8.1</td>
<td>1.4</td>
<td>-3.5</td>
<td>8.3</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Precipitation (mm)</td>
<td>34.3</td>
<td>20.1</td>
<td>19.6</td>
<td>25.5</td>
<td>40.8</td>
<td>44.5</td>
<td>38.1</td>
<td>36.7</td>
<td>26.1</td>
<td>22.2</td>
<td>33.1</td>
<td>35.9</td>
<td>376.8</td>
<td>-</td>
</tr>
<tr>
<td>Hedley Mine (T)</td>
<td>Daily Average (°C)</td>
<td>-7.4</td>
<td>-5.4</td>
<td>-2.9</td>
<td>2.9</td>
<td>5.5</td>
<td>8.8</td>
<td>12.6</td>
<td>12.3</td>
<td>9.0</td>
<td>3.4</td>
<td>-3.0</td>
<td>-6.1</td>
<td>2.5</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>Precipitation (mm)</td>
<td>51.1</td>
<td>43.3</td>
<td>38.6</td>
<td>40.6</td>
<td>63.3</td>
<td>69.2</td>
<td>49.2</td>
<td>46.3</td>
<td>33.7</td>
<td>36.4</td>
<td>48.0</td>
<td>55.4</td>
<td>575.0</td>
<td>0.69</td>
</tr>
<tr>
<td>Vernon (R)</td>
<td>Daily Average (°C)</td>
<td>-4.2</td>
<td>-1.2</td>
<td>3.8</td>
<td>8.5</td>
<td>13</td>
<td>17</td>
<td>19.7</td>
<td>19.6</td>
<td>14.3</td>
<td>7.9</td>
<td>1.2</td>
<td>-3.2</td>
<td>8.1</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Precipitation (mm)</td>
<td>32.8</td>
<td>26.2</td>
<td>26.9</td>
<td>27.7</td>
<td>40.1</td>
<td>42.4</td>
<td>37.5</td>
<td>33.8</td>
<td>32.9</td>
<td>26.6</td>
<td>40.4</td>
<td>42.7</td>
<td>409.9</td>
<td>-</td>
</tr>
<tr>
<td>Silver Star (T)</td>
<td>Daily Average (°C)</td>
<td>-6.1</td>
<td>-5.3</td>
<td>-2.7</td>
<td>1.4</td>
<td>4.6</td>
<td>9.8</td>
<td>14.0</td>
<td>13.7</td>
<td>10.2</td>
<td>1.9</td>
<td>-3.1</td>
<td>-7.0</td>
<td>2.6</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>Precipitation (mm)</td>
<td>112.1</td>
<td>95.7</td>
<td>88.0</td>
<td>46.8</td>
<td>12.8</td>
<td>49.4</td>
<td>40.6</td>
<td>36.4</td>
<td>41.5</td>
<td>75.1</td>
<td>101.1</td>
<td>134.3</td>
<td>833.7</td>
<td>0.56</td>
</tr>
<tr>
<td>McCulloch (R)</td>
<td>Daily Average (°C)</td>
<td>-7.7</td>
<td>-5.3</td>
<td>-1.9</td>
<td>2.5</td>
<td>7.1</td>
<td>10.5</td>
<td>13.1</td>
<td>13</td>
<td>8.7</td>
<td>3.5</td>
<td>-3.2</td>
<td>-7.4</td>
<td>2.74</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Precipitation (mm)</td>
<td>72.8</td>
<td>66.2</td>
<td>54.2</td>
<td>48.7</td>
<td>64.4</td>
<td>78.2</td>
<td>54.7</td>
<td>53.7</td>
<td>45.8</td>
<td>40.4</td>
<td>62.1</td>
<td>86.6</td>
<td>727.8</td>
<td>-</td>
</tr>
<tr>
<td>Big White (T)</td>
<td>Daily Average (°C)</td>
<td>-7.0</td>
<td>-5.3</td>
<td>-3.0</td>
<td>-0.4</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-5.1</td>
<td>-8.5</td>
<td>-</td>
<td>-</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>Precipitation (mm)</td>
<td>141.6</td>
<td>97.4</td>
<td>81.3</td>
<td>41.9</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>105.8</td>
<td>149.9</td>
<td>-</td>
<td>0.60</td>
</tr>
</tbody>
</table>
Table 3. Descriptive statistics of model performance for the simulation of maximum temperatures in Hedley Mine, Silver Star and Big White, at two different time scales.

<table>
<thead>
<tr>
<th>Comparison pair</th>
<th>Pair 1</th>
<th>Pair 2</th>
<th>Pair 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target site</td>
<td>Hedley Mine</td>
<td>Silver Star</td>
<td>Big White</td>
</tr>
<tr>
<td>Annual $T_{\text{max}}$ (Average ±SD)</td>
<td>Observed</td>
<td>Simulated</td>
<td>Observed</td>
</tr>
<tr>
<td></td>
<td>7.73 ± 9.45</td>
<td>6.92 ± 11.42</td>
<td>5.24 ± 9.92</td>
</tr>
<tr>
<td>Performance for</td>
<td>Monthly values $^2$</td>
<td>Daily values</td>
<td>Monthly values</td>
</tr>
<tr>
<td>$n$</td>
<td>12</td>
<td>7971</td>
<td>12</td>
</tr>
<tr>
<td>$r$</td>
<td>0.99</td>
<td>0.92</td>
<td>0.99</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.97</td>
<td>0.85</td>
<td>0.99</td>
</tr>
<tr>
<td>MER ($^\circ$C)</td>
<td>0.50</td>
<td>0.28</td>
<td>0.20</td>
</tr>
<tr>
<td>MAE ($^\circ$C)</td>
<td>1.43</td>
<td>3.36</td>
<td>1.52</td>
</tr>
<tr>
<td>ME</td>
<td>0.87</td>
<td>0.78</td>
<td>0.95</td>
</tr>
<tr>
<td>Theil’s $U$</td>
<td>0.27</td>
<td>0.35</td>
<td>0.18</td>
</tr>
</tbody>
</table>

$^1$ No years with full 12-month records were available at Big White (only winter months available).

$^2$ For each month of the year, average monthly maximum temperatures for the simulation years compared with the average of the observed monthly maximum temperatures.
Table 4. Descriptive statistics of model performance for the simulation of minimum temperature for each year in Hedley Mine, Silver Star and Big White, at two different time scales.

<table>
<thead>
<tr>
<th>Comparison Pair</th>
<th>Pair 1</th>
<th>Pair 2</th>
<th>Pair 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target site</td>
<td>Hedley Mine</td>
<td>Silver Star</td>
<td>Big White</td>
</tr>
<tr>
<td>Annual $T_{\text{min}}$ (Average ±SD)</td>
<td>Observed</td>
<td>Simulated</td>
<td>Observed</td>
</tr>
<tr>
<td>Observations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$n$</td>
<td>12</td>
<td>8114</td>
<td>12</td>
</tr>
<tr>
<td>$r$</td>
<td>0.99</td>
<td>0.87</td>
<td>0.99</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.98</td>
<td>0.76</td>
<td>0.98</td>
</tr>
<tr>
<td>MER (°C)</td>
<td>-0.12</td>
<td>-0.81</td>
<td>-0.23</td>
</tr>
<tr>
<td>MAE (°C)</td>
<td>0.99</td>
<td>0.82</td>
<td>0.80</td>
</tr>
<tr>
<td>ME</td>
<td>0.97</td>
<td>0.77</td>
<td>0.97</td>
</tr>
<tr>
<td>Theil’s $U$</td>
<td>0.16</td>
<td>0.51</td>
<td>0.16</td>
</tr>
</tbody>
</table>

1 No years with full 12-month records were available at Big White (only winter months available).

2 For each month of the year, average monthly minimum temperatures for the simulation years compared with the average of the observed monthly minimum temperatures.
Table 5. Descriptive statistics of model performance for the simulation of precipitation in Hedley Mine, Silver Star and Big White at two different time scales.

<table>
<thead>
<tr>
<th>Comparison Pair</th>
<th>Annual P</th>
<th>Performance for Monthly values&lt;sup&gt;2&lt;/sup&gt;</th>
<th>Performance for Daily values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target site</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hedley Mine</td>
<td>Observed</td>
<td>12</td>
<td>7751</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>713.83 ± 183.11</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.31</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.10</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Silver Star</td>
<td>Observed</td>
<td>704.52 ± 225.70</td>
<td>0.65</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>789.37 ± 152.35</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.43</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Big White</td>
<td>Observed</td>
<td>-11.25</td>
<td>9.26</td>
</tr>
<tr>
<td></td>
<td>Simulated</td>
<td>1237.88 ± 212.51</td>
<td>2.52</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<sup>1</sup> No years with full 12-month records were available at Big White (only winter months available).

<sup>2</sup> For each month of the year, average monthly minimum temperatures for the simulation years compared with the average of the observed monthly minimum temperatures.
Table 6. Equivalence tests for daily and monthly values of maximum and minimum temperature and precipitation. A rejection of the null hypothesis of dissimilarity means that both population of simulated and recorded data are not distinguishable and can be considered equivalent.

<table>
<thead>
<tr>
<th>Time scale</th>
<th>Variable</th>
<th>Target site</th>
<th>$t_d$</th>
<th>Strict test (absolute bias &lt; 25% SD)</th>
<th>Relaxed test (absolute bias &lt; 50% SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>$T_{\text{MAX}}$</td>
<td>Hedley Mine</td>
<td>14.83</td>
<td>426.59</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Silver Star</td>
<td>-9.18</td>
<td>68.08</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Big White</td>
<td>-34.13</td>
<td>47.24</td>
<td>Rejected</td>
</tr>
<tr>
<td>Daily</td>
<td>$T_{\text{MIN}}$</td>
<td>Hedley Mine</td>
<td>5.38</td>
<td>434.86</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Silver Star</td>
<td>-22.11</td>
<td>67.40</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Big White</td>
<td>-47.09</td>
<td>50.77</td>
<td>Rejected</td>
</tr>
<tr>
<td>Monthly</td>
<td>$T_{\text{MAX}}$</td>
<td>Hedley Mine</td>
<td>2.35</td>
<td>6.29</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Silver Star</td>
<td>-3.03</td>
<td>0.12</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Big White</td>
<td>4.13</td>
<td>0.11</td>
<td>Not Rejected</td>
</tr>
<tr>
<td>Monthly</td>
<td>$T_{\text{MIN}}$</td>
<td>Hedley Mine</td>
<td>-5.94</td>
<td>6.26</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Silver Star</td>
<td>-4.15</td>
<td>0.12</td>
<td>Not Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Big White</td>
<td>-5.62</td>
<td>0.11</td>
<td>Not Rejected</td>
</tr>
<tr>
<td>Monthly</td>
<td>$P$</td>
<td>Hedley Mine</td>
<td>5.81</td>
<td>0.22</td>
<td>Not Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Silver Star</td>
<td>6.17</td>
<td>0.10</td>
<td>Not Rejected</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Big White</td>
<td>9.34</td>
<td>0.06</td>
<td>Not Rejected</td>
</tr>
</tbody>
</table>
Figure 1.
Figure 2.
Figure 3.
Figure 4.
Figure 5.
Figure 6.
Figure 7.
**Figure 8.**

**Figure 9.**