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DEVELOPMENT OF SCALE-FREE CLIMATE DATA FOR WESTERN CANADA FOR USE IN RESOURCE MANAGEMENT

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ABSTRACT

Applying climate data in resource management requires matching the spatial scale of the climate and resource databases. Interpolating climate data in mountainous regions is difficult. In this study, we present methodology to generate scale-free climate data through the combination of interpolation techniques and elevation adjustments. We apply it to monthly temperature and precipitation normals for 1961–90 produced by the Parameter-elevation Regressions on Independent Slopes Model (PRISM) for British Columbia, Yukon Territories, the Alaska Panhandle, and parts of Alberta and the United States. Equations were developed to calculate biologically relevant climate variables including various degree-days, number of frost-free days, frost-free period, and snowfall from monthly temperature and precipitation data. Estimates of climate variables were validated using an independent dataset from weather stations that were not included in the development of the model. Weather station records generally agreed well with estimated climate variables and showed significant improvements over original PRISM climate data. A stand-alone MS Windows application was developed to perform all calculations and to integrate future climate predictions from various global circulation models. We demonstrate the use of this application by showing how climate change may affect lodgepole pine seed planning zones for reforestation in British Columbia. Copyright © 2006 Royal Meteorological Society.

KEY WORDS: PRISM; derived climate variables; climate change; forest management; British Columbia

1. INTRODUCTION

Climate is the primary factor controlling the distribution of plants (Tuhkanen, 1980; Woodward, 1987; Woodward and Williams, 1987). It is also the major factor affecting the adaptation and productivity of forest trees (McKenney and Pedlar, 2003; Rehfeldt, 1995; Rehfeldt *et al*., 2002; Rehfeldt *et al*., 2001; Rehfeldt *et al*., 1999). Therefore, a good understanding of plant–climate relationships is essential in forestry for formulating effective strategies for species conservation and seed deployment. To avoid maladaptation and ensure maximum forest productivity in forest plantations, the climate of sites of the seed origin of forestry planting stock and the sites to which they are deployed must be similar. The prospect of climate change complicates these relationships and is expected to alter species habitat (Dirnbock *et al*., 2003; Eeley *et al*., 1999; Iverson and Prasad, 1998) and productivity (Rehfeldt *et al*., 2004; Rehfeldt *et al*., 2001). Lack of reliable climate data has limited investigations in this area and has sometimes resulted in misleading conclusions (Hamann and Wang, 2004).

Applying climate data in resource management requires matching the spatial scale of the climate and resource databases. Climate normals are the arithmetic mean of weather measurements from weather station records over three consecutive decades (WMO, 1989). Because of the limited numbers of weather stations,

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climate normals for locations of interest, such as plantations, test sites, and parent tree origins, are often estimated through interpolation of normals from existing stations. However, the sparse distribution of weather stations introduces considerable error when interpolating in mountainous areas, and there is a lack of biologically relevant variables, such as growing degree-days (DD) and frost-free period (FFP). One widely used interpolation method is Parameter-elevation Regressions on Independent Slopes Model (PRISM). Gridded climate data generated by PRISM are available for the United States and parts of Canada at resolutions of 2.5 and 1.25 arcmin respectively for the reference period 1961–1990 (Daly *et al.*, 2002a). However, because PRISM climate estimates are based on each tile's average elevation, there may be discrepancies of up to 1200 m in mountainous areas between the PRISM tile elevation and the actual elevation of specific locations within the tiles. Elevational differences of this magnitude can result in large differences between predicted and observed values, particularly for temperature variables. In addition, there is a need for derived climate variables such as growing DD and FFP, which operate most directly in natural selection (Tuhkanen, 1980) and are therefore relevant in ecological and genecological studies.

The area of western Canada evaluated in this study is about 150 Mha with a PRISM grid size of approximately 4 × 4 km. In a previous study, the low-resolution problem was partially solved using elevation adjustment to significantly improve PRISM predictions (Hamann and Wang, 2004). However, to generate seamless geographical surfaces at high resolution, additional up-scaling techniques are required, effectively resulting in scale-free climate data. The up-scaling procedure forms the first part of this study. In the second part, equations are developed from scale-free monthly data to estimate widely used, biologically relevant derived climate variables, such as growing DD, frost-free-period, snowfall, and growing season length. In the third part of this study, data from scenarios from several Global Circulation Models (GCMs) were combined with our high-resolution reference period surfaces to predict future climate surfaces. In application an example, we demonstrate how climate change may affect the climate of current seed zones for British Columbia. In addition, observed climate changes since the reference period (1961–1990) were also integrated into the scale-free climate data. The observed changes are of special interest to ecologists and resource managers because they have the potential to explain recent ecological changes (Woods *et al.*, 2005). We have developed a stand-alone MS Windows computer application to perform the up-scaling process, calculate derived climate variables, and add climate change predictions from a variety of GCM for any desired point location, defined by latitude, longitude, and elevation in the study area.

2. METHODS

2.1. Climate data

The PRISM dataset used in this study was developed by the Spatial Climate Analysis Service of Oregon State University for the Canadian and BC provincial governments using the 1961–1990 weather station normals. It covers the region (Figure 1) between 47 and 70 °N in latitude and between 113 and 141 °W in longitude, which includes British Columbia, the Yukon, and parts of Alberta, the continental USA, and Alaska. The dataset consists of gridded (2.5 arcmin) estimates of monthly average, maximum, and minimum air temperature and monthly precipitation (i.e. 4 variables × 12 months = 48 'base' variables), as well as average grid tile elevations.

Predictions of changes to each of the base variables were obtained from Canadian Impacts and Scenarios Project (2005), including six ensemble averages generated by six global circulation models: CGCM1gax, CGCM2-A2x, and CGCM2-B2x of the Canadian Centre for Climate Modeling and Analysis (Flato *et al.*, 2000) and HADCM2-gax, HADCM2-ggx, and HADCM3-A2x of the Hadley Centre (Johns *et al.*, 1997; Johns *et al.*, 2003). These models make change predictions in the temperature and precipitation normals for the 2020s, 2050s, and 2080s. Because different climate change models use different prediction locations and different resolution, we interpolated these coverages to a standardized 1° latitude by 1° longitude grid using ANUspline (Hutchinson, 1989).

Observed changes since the reference period (1961–1990) were represented by the differences between the climate normals of the reference period and 5-year averages for the period from 1998 to 2002. Observed

Figure 1. The coverage of the PRISM data (shaded area) used in this study

changes in precipitation and temperature variables (Mekis and Hogg, 1999; Vincent *et al.*, 2002) at 70 weather stations covering western Canada were interpolated at 1° resolution using ANUSpline to generate an additional dataset of observed changes similar to methods used for predictions from the GCM datasets.

2.2. Developing PRISM-based scale-free climate data

Instead of applying the midpoint values of each 4 × 4-km PRISM tile to all points within each tile, we used bilinear interpolation method to interpolate values between midpoints of the 4 × 4-km grids (Figure 2):

$$f(P) = t_1 d_2 d_4 + t_2 d_1 d_4 + t_3 d_2 d_3 + t_4 d_1 d_3 \tag{1}$$

where $f(P)$ is the interpolated value of the point P; t_1, t_2, t_3, and t_4 are PRISM midpoint's values (including climate variables and elevation) of the four nearest tiles of the point P; d_1, d_2, d_3, and d_4 are relative distances. Bilinear interpolation can be viewed as a two-step process. It performs linear interpolation in one direction (between t_1 and t_2 for P_1 and between t_3 and t_4 for P_2) first and then in the other direction (between P_1 and P_2 for P) as illustrated in Figure 2.

Through bilinear interpolation, the 4 × 4-km PRISM grids are translated into a continuous surface while the original values at each PRISM tile's midpoint remain unchanged. The result can be imagined as a surface of tilted 4 × 4-km tiles anchored at midpoints of PRISM tiles. Instead of having a sharp step from tile to tile, we have a scale-free gradient from the midpoint of one tile to the next. Therefore, specific estimates of all climate variables and elevation can be obtained for any locations within each PRISM tiles, and the predictions are formula-based (no data set is generated) and scale-free.

Following the bilinear interpolation step, elevation adjustment was then applied to interpolated climate values, as described in our previous study (Hamann and Wang, 2004) for annual climate data. In this study, we developed additional polynomial functions for each monthly temperature variable based on geographic coordinates (latitude, longitude, and elevation) and their combinations and transformations as independent

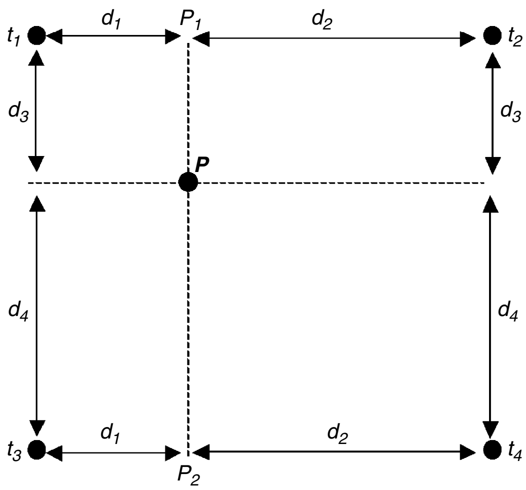

Figure 2. Illustration of bilinear interpolation of the PRISM data. P is the location for prediction; t_1, t_2, t_3, and t_4 are the values of climate variables at the centers of the four neighboring PRISM tiles; d_1, d_2, d_3, and d_4 are the relative spatial distances. P_1 and P_2 are predictions based on simple linear interpolations of the climate variable values t_1 and t_2, and t_3 and t_4, respectively

variables using PRISM data (over 150 000 interpolated observations). We then took the partial derivative of this function with respect to elevation to obtain the partial differential equation, which is the rate of change in a temperature variable (environmental lapse rate) in response to a change in elevation for any given latitude, longitude, and elevation. The amount of elevation adjustment for a given site is the partial differential equation multiplied by the difference between the site elevation and bilinear interpolated PRISM tile elevation. The relationships between precipitation variables and these independent variables were not strong enough to allow us to develop elevation-adjustment functions for precipitation variables.

2.3. *Testing the scale-free climate variable estimates*

The quality of all climate variable estimates was evaluated through the comparison between predicted and observed climate data at weather stations using an independent weather station dataset. PRISM data were developed using weather station normals for the period 1961–1990. The independent dataset consisted of records from 191 weather stations (Figure 3(B)) that had sufficient records to be included in the 1951–1980 normals but were discontinued or had too short a record to be included in the official 1961–1990 dataset. Improvements of predictions using scale-free climate data relative to original PRISM data were evaluated by changes to the variance explained in observed climate data and by changes to the standard errors of predictions. Minor differences in temperature and precipitation between the 1961–1990 and the 1951–1980 data sets are not expected to cause biased evaluation, as the differences should mostly affect the intercept of a linear relationship rather than the amount of variance explained and standard errors.

2.4. *Developing derived variables*

Biologically relevant and other widely used climate variables were calculated or derived from the PRISM-based scale-free monthly climate normal data. Seasonal climate variables are simple averages (for temperatures, in °C) or sums (for precipitation, in millimeters) of monthly data for each season. Directly calculated annual variables include: mean annual temperature (MAT: the average over monthly mean temperatures), mean warmest month temperatures (MWMT), mean coldest month temperatures (MCMT), temperature difference between MWMT and MCMT (TD), mean annual precipitation (MAP: sum of monthly precipitation), summer precipitation (MSP: sum of monthly precipitation from May through September), annual heat/moisture index (AHM: (MAT + 10)/(MAP × 1000)) and summer heat/moisture index (SHM: MWMT/(MSP × 1000)) (Tuhkanen, 1980).

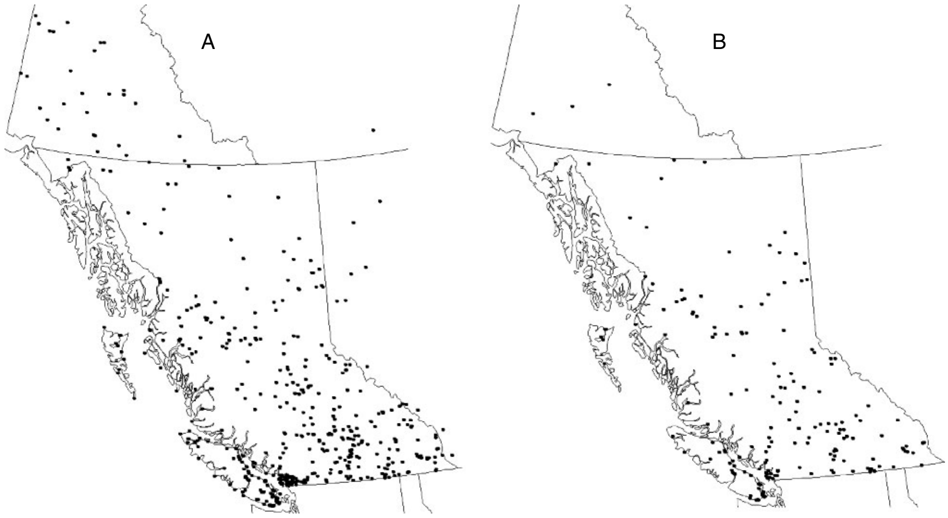

Figure 3. Locations of 493 (A) and 191 (B) weather stations, from which climate normals were used for development of derived climate variables and assessment of downscaled PRISM data, respectively

Additional climate variables that could not be directly calculated from PRISM data were estimated with linear or nonlinear regression techniques developed from direct observations (1951–1980 normals) at 493 weather stations (Figure 3(A)) throughout the study area.

2.4.1. Degree-days. Degree-days for a given day represent the accumulated temperature sum of Celsius degrees per day that the mean temperature is above or below a given base. The annual DD are the sum of daily DD over a year (degree-days are referred to as annual degree-days hereafter, unless specified). The observed degree-days (DD_{ob}) at weather stations are calculated as

$$DD_{\mathrm{ob}} = \sum_{1}^{12}\sum_{1}^{n}(T_i - base) \quad \text{for } T_i > base \tag{2}$$

$$DD_{\mathrm{ob}} = \sum_{1}^{12}\sum_{1}^{n}(base - T_i) \quad \text{for } T_i < base, \tag{3}$$

where n is the number of days in the month and T_i is the daily mean temperature. Equation (2) is for calculating DD above a given base and (3) for DD below a given base. Since PRISM data sets do not include daily temperatures, Equations (2) and (3) were modified as follows for using monthly mean temperature (T_{m}) for estimated degree-days (DD_{est}):

$$DD_{\mathrm{est}} = \sum_{1}^{12}(T_{\mathrm{m}} - base) \times N_m \quad \text{for } T_{\mathrm{m}} > base \tag{4}$$

$$DD_{\mathrm{est}} = \sum_{1}^{12}(base - T_{\mathrm{m}}) \times N_m \quad \text{for } T_{\mathrm{m}} < base. \tag{5}$$

where N_m is the number of days in the m^{th} month, and $m = 1, 2, \ldots, 12$. These modifications may result in bias as some months with $T_{\mathrm{m}} < base$ may have some days with mean temperature (T_i) above the *base* and vice versa (Wendland, 1983). Therefore, corrections were applied on the basis of the following linear regression model:

$$DD_{\text{ob}} = a + bDD_{\text{est}} \tag{6}$$

where a is the intercept and b is the regression coefficient.

Degree-days estimated in this study include: (1) DD above 5 °C (DD > 5 °C), (2) DD below 0 °C (DD < 0 °C), (3) DD above 18 °C (DD > 18 °C), and (4) DD below 18 °C (DD < 18 °C). DD > 5 °C and DD < 0 °C are often used in forestry and agriculture as an index of meeting plant growth and chilling requirements, thus they are also referred as *growing DD* and *chilling DD*, respectively. Degree-days above or below the base of 18 °C are used primarily to estimate the cooling and heating requirements of buildings, thus they are called *cooling and heating DD*, respectively. Equation (4) was, however, not suitable for estimating DD > 18 °C because there were a number of weather stations where the monthly mean temperature was always below the base, even though there were some DD reported. Thus, DD > 18 °C was estimated on the basis of a nonlinear relationship with July mean temperature:

$$DD > 18^{\circ}C_i = \frac{a}{1 + e^{-(T_i - T_0)/b)}}, \tag{7}$$

where *a, b and* T_0 are the parameters to be estimated.

The day of the year on which accumulated growing DD (DD > 5 °C) reach 100 ($DD5_{100}$) corresponds to the approximate date of budburst of some forest trees, which can be used as a general indicator for the beginning of growing season although substantial variation exists among species. We estimated the date assuming that the increase in DD > 5 °C from one month to the next is linearly related to the corresponding increase in day of the year. Thus, it was estimated as

$$DD5_{100} = ED_{\text{below}} + (ED_{\text{above}} - ED_{\text{below}}) \times (100 - DD5_{\text{below}})/(DD5_{\text{above}} - DD5_{\text{below}}). \tag{8}$$

where ED_{below} and ED_{above} are the days of the year at the ends of the months, on which the accumulated DD > 5 °Cs are just below and above 100 respectively; $DD5_{\text{below}}$ and $DD5_{\text{above}}$ are accumulated DD > 5 °Cs at the ends of the months when the accumulated DD > 5 °C are just below and above 100 respectively.

2.4.2. Number of frost-free days (NFFD). NFFD was modeled on the basis of a nonlinear relationship between proportions of monthly NFFD and monthly minimum temperature (Figure 4) using the sigmoid function:

$$P_i = \frac{1}{1 + ae^{-(T_i \times b)}}, \tag{9}$$

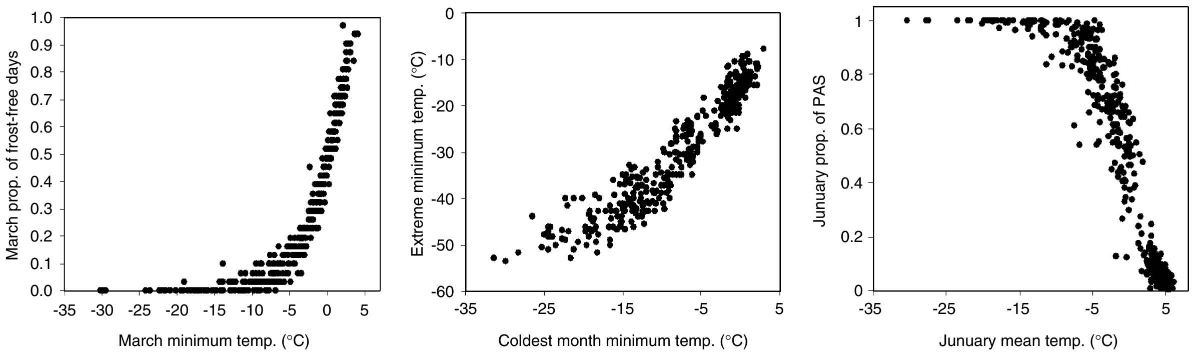

Figure 4. Nonlinear relationships between some biologically relevant climate variables and monthly temperatures. PAS is precipitation as snow

where P_i is the proportion of monthly NFFD, T_i is the monthly minimum temperature, and a and b are parameters to be estimated. P_i was then converted to monthly NFFD by multiplying by the number of days in the month, and then summed over 12 months to calculate the annual data. Corrections were also applied as for DD.

2.4.3. Frost-free period (FFP). FFP is the number of *consecutive* frost-free days, and was calculated on the basis of the day of the year on which FFP begins (bFFP) and FFP ends (eFFP). bFFP and eFFP were estimated using the same principle as was used for estimating $DD5_{100}$, assuming daily temperature increase in spring or decrease in fall from one month to the next is linearly related to the corresponding increase in day of the year. They were calculated as

$$bFFP = MD_{\text{below}} + (MD_{\text{above}} - MD_{\text{below}}) \times (T_0 - T_{\text{below}})/(T_{\text{above}} - T_{\text{below}}) \tag{10}$$

$$eFFP = MD_{\text{above}} + (MD_{\text{below}} - MD_{\text{above}}) \times (T_{\text{above}} - T_0)/(T_{\text{above}} - T_{\text{below}}) \tag{11}$$

where MD_{below} and MD_{above} are the days of the year for the mid-date of the months when the mean monthly temperatures are just below (T_{below}) and above (T_{above}) the threshold T_0 respectively. FFP was then calculated by subtracting bFFP from eFFP.

2.4.4. Extreme minimum temperature (EMT). Extreme minimum temperature (EMT) refers to the record minimum temperature at a weather station (over 30 years). It was modeled using the four-parameter sigmoid function to reflect the nonlinear relationship with the minimum temperature of the coldest month in a year (Figure 4):

$$EMT = y_0 + \frac{a}{1 + e^{-(T - x_0)/b}} \tag{12}$$

where y_0, x_0, a and b are parameters to be estimated, and T is the minimum temperature of the coldest month in a year.

2.4.5. Precipitation as snowfall (PAS). PAS was modeled on the basis of a nonlinear relationship between monthly proportion of *PAS* and monthly mean temperature (Figure 4) using the following two-parameter sigmoid function:

$$P_i = \frac{1}{1 + e^{-(T_i - x_0)/b}}, \tag{13}$$

where P_i is the monthly proportion of precipitation as snowfall (PAS) (water equivalent), x_0 and b are parameters to be estimated, and T_i is the monthly mean temperature. P_i was then converted to PAS by multiplying by the amount of precipitation in the month, and summed over the year to calculate the annual amount.

The derived climate variables were evaluated after the functions were applied to PRISM-based scale-free monthly data. The evaluation was based on the amount of variance explained and the standard errors of the climate variable estimates against the 1951–1980 normals from the 493 weather stations for all derived variables except $DD5_{100}$, bFFP, and eFFP. These three variables were evaluated using a dataset from a fewer number of weather stations because they were not available for all of the weather stations. We extracted observed monthly DD > 5 °C from 139 stations for evaluating $DD5_{100}$. 'Observed' $DD5_{100}$ was actually estimated using the Equation (8) based on observed monthly DD > 5 °C (*vs* estimated monthly DD > 5 °C). Observed bFFP and eFFP were extracted from 136 weather stations.

3. RESULTS AND DISCUSSION

3.1. Elevation-adjustment functions

The polynomial functions developed using geographic variables (latitude, longitude, and elevation) to model monthly temperature variables based on PRISM data were all statistically significant ($p < 0.0001$). Most of the functions explained more than 90% of the total variation in PRISM data, which provided a solid basis for the development of effective elevation-adjustment functions (Figure 5). The modeling of temperatures for the colder months (October–March) resulted in higher R^2 values than those for the warmer months (May–August), and it is particularly pronounced in T_{min}. This is consistent with previous studies either directly using weather station data ($R^2 = 0.81$) (Rehfeldt *et al.*, 1999) or using PRISM data ($R^2 = 0.86$) (Hamann and Wang, 2004) for mean warmest month temperature. This is probably due to reduced geographical variation of temperature variables in summer months (e.g. coefficients of variation among weather stations for July T_{max} and T_{min} are less than a third of those for January). After additions of two second-order transformations of geographic coordinates (i.e. latitude^2 × elevation and longitude^2 × elevation) to the list of independent variables not used in previous studies (Hamann and Wang, 2004; Rehfeldt *et al.*, 1999), R^2 of the models for monthly maximum and mean temperatures were considerably improved. However, the R^2 remained relatively low for monthly minimum temperatures of June, July, and August, even with third-order transformations of geographic coordinates into the models.

For precipitation, elevation adjustment is not promising because the physical relationship between precipitation and elevation is more complicated than that between temperatures and elevation. Nonetheless, we tested the same methodology used for temperature variables and found that geographical variables can maximally explain only 65% of the total variation in precipitation (*vs* over 90% for temperature variables). Although the amount of error of the predictions for weather stations could be related to the elevational difference between weather stations and PRISM tile center, we believe that this is an artifact resulting from the distribution of stations in British Columbia. The relationship is mainly driven by coastal stations and weather stations on the leeward side of interior mountain ranges, where precipitation increases with elevation. However, increase of precipitation with elevation only occurs from base to mid-slopes of mountains because of orographic lift

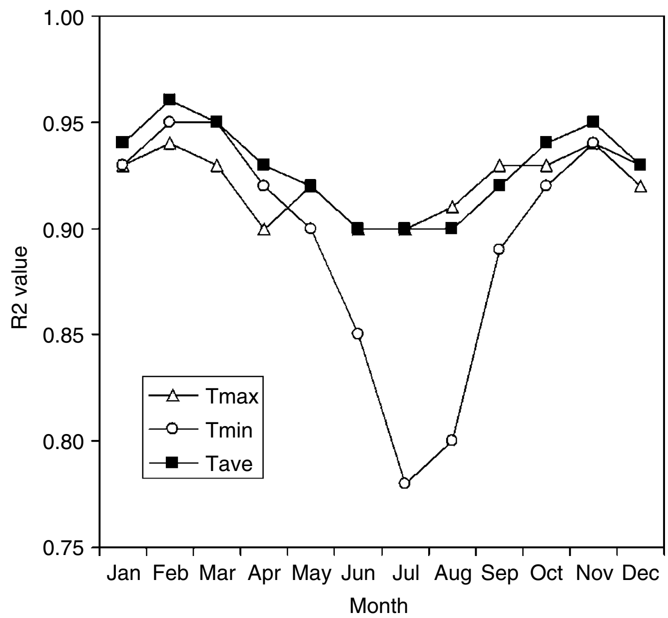

Figure 5. Values of R^2 for polynomial functions modeling monthly maximum (T_{max}), minimum (T_{min}) and mean (T_{ave}) temperatures of PRISM data using geographic variables including latitude, longitude, elevation, and their transformations and combinations

and does not continue to increase further up the slope, and thus cannot be generalized (Daly *et al.*, 2002a). Consequently, elevation adjustment for precipitation was not applied in this study.

3.2. Improvement in predictions

Predictions of basic climate variables for the 191 independent weather stations were considerably improved over original PRISM data in term of the increase in total variances explained in the weather station data (Figure 6) and decreased standard errors of predictions (Table I). The improvements were the greatest for monthly maximum temperatures (10% increase in the variance explained and 31% decrease in standard error, on average) followed by monthly average temperatures (7% increase and 31% decrease). Improvements for monthly minimum temperatures (2% increase and 14% decrease) and monthly precipitation were minimal (1% increase and 14% decrease). For monthly precipitation, the limited improvement is the result of smoothing by bilinear interpolation, because no elevation adjustment was applied to this variable.

The degree of improvement in predictions varied considerably among months (Figure 6 and Table I). The original PRISM data predict observed temperature variables well at weather stations for the colder months, from November through February, with values of R^2 greater than 0.95. Therefore, improvements of predictions using scale-free climate data are limited for these months. For other months, predictions of temperature variables directly using the PRISM data were generally poor, particularly for the warmer months from April through August, which left room for improvement by as much as 22% in variance explained (Figure 6). The better predictions by PRISM for temperatures in colder months are due to the small lapse rates of temperatures with elevation for these months, translating even large elevation differences into rather small temperature changes. In contrast, during summer, large lapse rates maximized the elevation-caused errors, resulting in large improvements when elevational downscaling was used.

The level of improvement in predictions was generally greater for standard errors than for variance explained. For monthly precipitation, in particular, the improvement through bilinear interpolation was 14% in term of reduced standard error compared to 1% for the increase in variance explained. This is because the variance explained also depends on the range of environments sampled. A few millimeters of reduction in standard error is relatively small compared to the large variation in precipitation across the whole sample area. Therefore, for quantifying improvement, standard error is the most important measure. This also likely applies to temperature variables. Bilinear interpolation accounted for about 1% of the increase in explained variance for all temperature variables. However, it might have greater contribution to the decreases in standard errors.

Table I. Standard error of predictions for monthly climate variables including maximum (T_{max}), minimum (T_{min}) and average (T_{ave}) temperatures and precipitation (PPT) with PRISM data and PRISM-based scale-free (PSF) climate model

Month	T_{max}		T_{min}		T_{ave}		PPT	
	Prism	PSF	Prism	PSF	Prism	PSF	PRISM	PSF
January	1.3	1.1	1.7	1.6	1.4	1.3	29.8	23.5
February	1.0	0.8	1.4	1.2	1.1	0.8	21.0	15.6
March	1.3	0.8	1.3	1.0	1.1	0.7	20.4	13.6
April	1.4	0.8	1.1	0.8	1.1	0.7	12.4	10.3
May	1.5	0.9	1.1	0.9	1.2	0.7	7.6	7.3
June	1.4	0.9	1.1	0.9	1.1	0.7	9.5	8.7
July	1.4	0.9	1.2	1.0	1.1	0.7	7.2	8.5
August	1.3	0.9	1.2	1.1	1.2	0.7	11.5	9.7
September	1.2	0.8	1.2	1.1	1.2	0.7	12.5	10.6
October	1.1	0.8	1.1	1.0	1.0	0.7	34.6	20.2
November	1.0	0.7	1.2	1.0	1.0	0.7	26.2	19.3
December	1.3	1.1	1.7	1.5	1.4	1.2	30.2	22.0
Average	1.27	0.88	1.28	1.09	1.16	0.80	18.58	14.11
Change %	−31		−14		−31		−14	

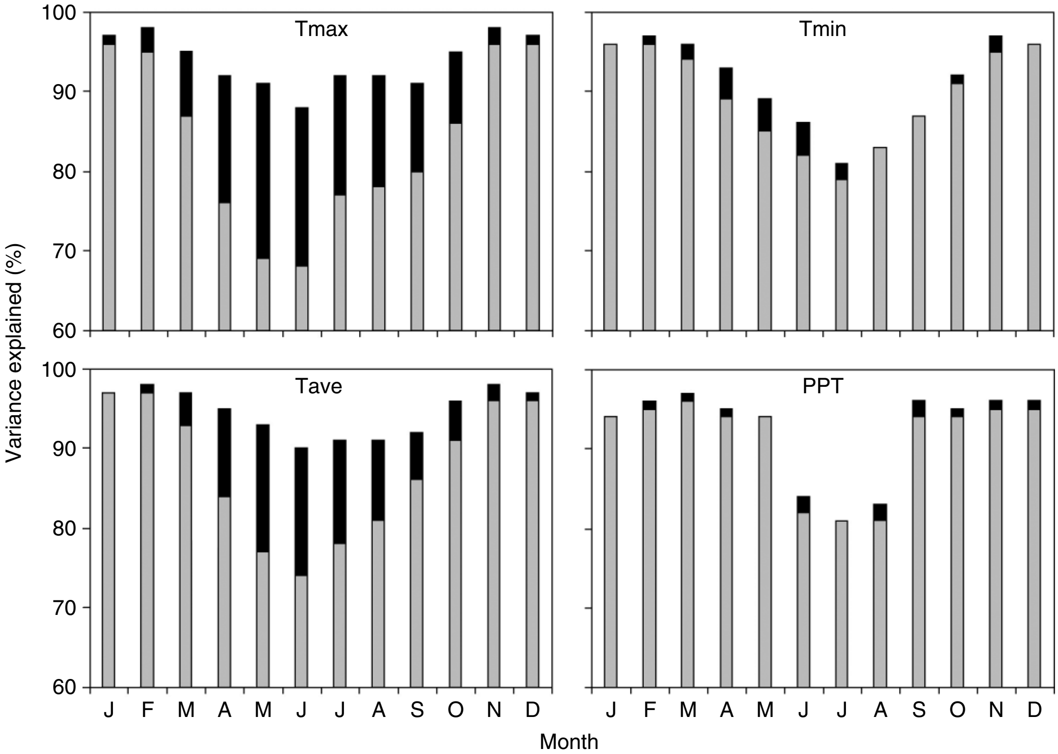

Figure 6. The amount of variance (%) explained in weather station data by predictions using original PRISM data (■) and PRISM-based scale-free climate data (■ + ■) for monthly maximum (A), monthly minimum (B) and monthly average (C) temperatures, and monthly precipitation (D)

For example, the improvement achieved in standard errors through the combination of bilinear interpolation and elevation adjustment was between 14 and 31% for temperature variables. This is substantially greater than the improvements of between 8 and 27% achieved through elevation adjustment alone in our previous study (Hamann and Wang, 2004).

The improvement of predictions by using scale-free climate data can also be visualized on maps of predicted climate variables, using mean annual temperature predicted for an area near Vancouver (Figure 7). The original PRISM estimates are displayed in Figure 7(A). Elevational adjustment of PRISM data improved the predictions (Figure 7(B)), but the boundaries among the original PRISM tiles are still visible. The reason for this is that differences among adjacent PRISM tiles are not entirely determined by elevation (Daly *et al.*, 2002b). Thus, elevation adjustments based on single tiles are not a perfect replacement for original PRISM methodology and steps occur at the boundaries between neighboring tiles. These steps can be problematic for many projects, particularly those involving high-resolution GIS maps or studies involving small geographic areas. For instance, two nearby sampling locations with identical climate, but on different PRISM tiles, could deviate substantially. The combination of bilinear interpolation and elevation adjustment overcame this problem and produced a smooth surface of predicted mean annual temperature that matches the topographic surface and the associated temperature gradients (Figure 7(C)).

3.3. Evaluation of derived variables

We evaluated derived variables at several points in their development. As a detailed example, DD above 5 °C (DD > 5 °C), estimated with Equation (4) based on normals from 493 weather stations, were linearly related to observed DD > 5 °C with a 'Model fit R^2' of 0.993 ($p < 0.0001$), a slope of 1.0302, and an intercept of 81. Thus, estimated DD > 5 °C was then corrected using Equation (6) by multiplying the slope

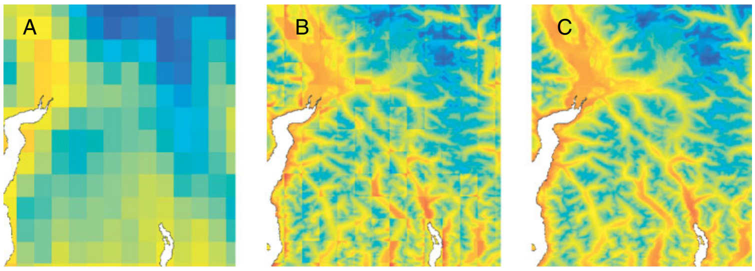

Figure 7. Maps of mean annual temperature predicted by PRISM data (A), elevation-adjusted PRISM data (B) and the combination of bilinear interpolation and elevational adjustment (C) for a 50 × 50 km area (mid point LAT = 49°41′29″N and LONG = 123°8′38″) near Vancouver based on a high-resolution digital elevation model (100 × 100 m)

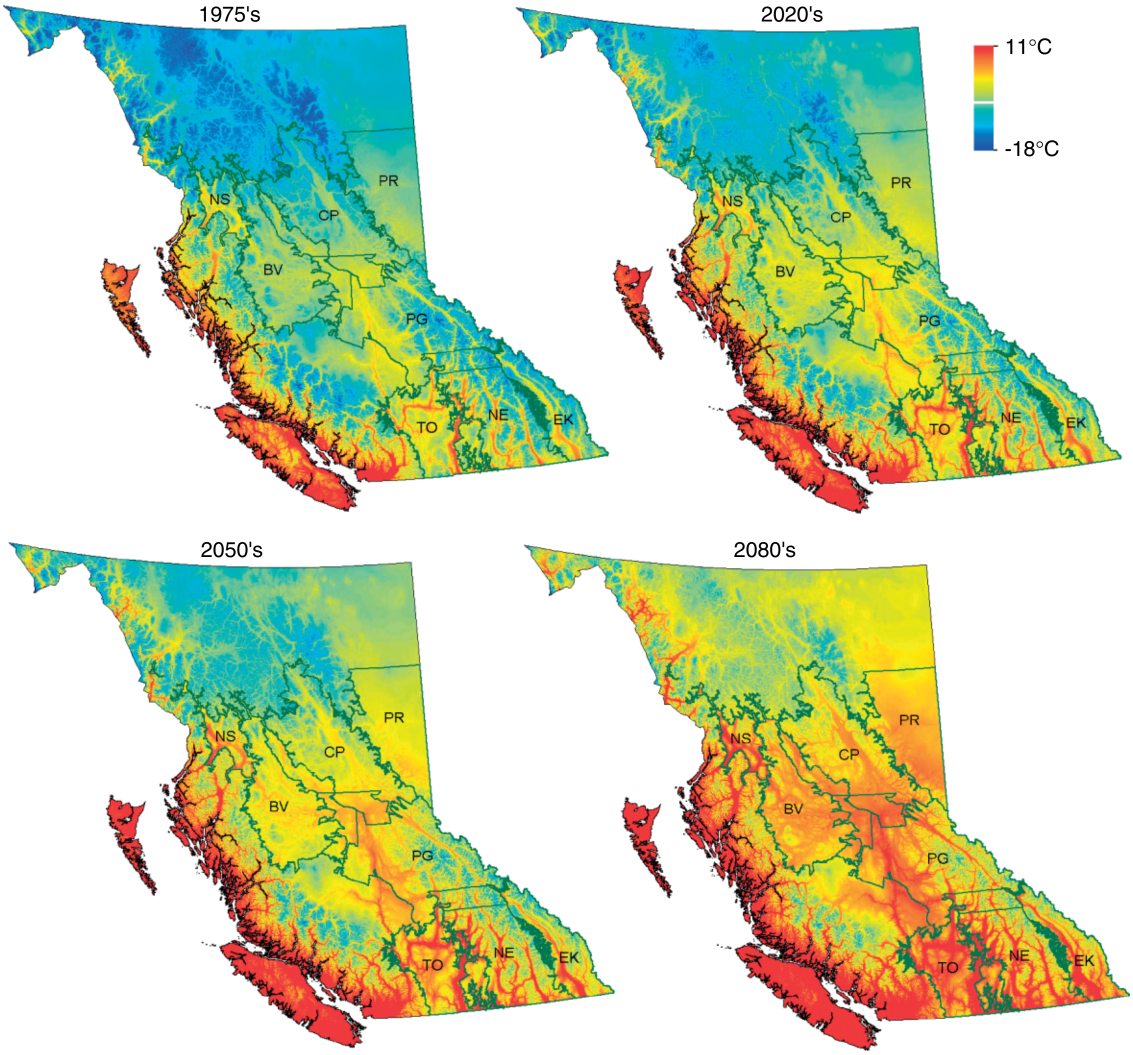

Figure 9. Maps of lodgepole pine seed planning zones overlaid to mean annual temperature for reference period (1961–1990) and predicted for the 2020s, 2050s and 2080s. For abbreviations of seed zones refer to Table III

and adding the intercept. The relationship between estimated and observed DD > 5 °C is shown in Figure 8, indicating this variable can be reliably predicted using mean monthly temperatures. The model fit for all degree-day variables (i.e. DD < 0 °C, DD > 5 °C, DD < 18 °C, and DD > 18 °C) and the number of frost-free days (NFFD) was almost perfect, with $R^2 \geq 0.99$ (Figure 8 and Table II). This is not surprising as very strong relationships between DD calculated from daily temperature and from monthly temperature have been reported in a previous study (Tuhkanen, 1980). FFP, EMT, and precipitation as snow (PAS) were also well modeled ($0.90 \leq R^2 \leq 0.96$). Standard errors of the estimates were also small (Table II – model fit).

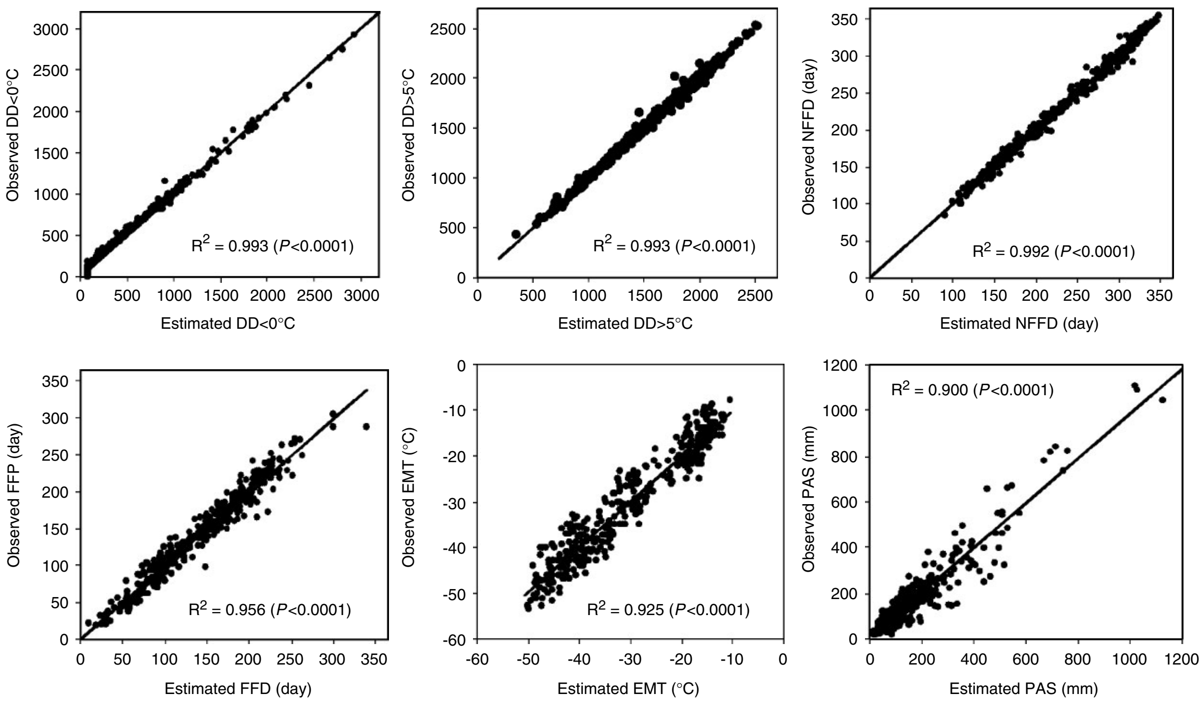

Figure 8. Relationships between observed and estimated climate variables, including DD < 0 °C (DD < 0 °C), DD > 5 °C (DD > 5 °C), number of frost-free days (NFFD), frost-free period (FFP), extreme minimum temperature (EMT), and precipitation as snow (PAS)

Table II. Variance explained (R^2) and standard error of predictions for weather station data (model fit) and PRISM-based scale-free climate data

Variable	Model fit using weather station data		Precision of scale-free prediction	
	R^2	Standard error	R^2	Standard error
Degree-days <0 °C	0.993	40	0.968	99
Degree-days >5 °C	0.993	27	0.919	122
Degree-days <18 °C	0.999	30	0.969	153
Degree-days >18 °C	0.988	7	0.851	18
$DD5_{100}$	–	–	0.95	4.6
Number of frost-free days	0.992	5	0.933	17
Frost-free period	0.956	10	0.853	21
bFFP	–	–	0.86	9.1
eFFP	–	–	0.90	11.6
Extreme minimum temperature	0.925	2.8	0.884	3.9
Precipitation as snow	0.900	32	0.855	64

After applying the models, established on the basis of weather station data, to PRISM-based scale-free monthly data for evaluation, the relationship between estimated and observed values are somewhat comprised (Table II – precision of estimates), with the value of R^2 reduced by about 0.07. Standard errors of the estimates were also increased. This is not a surprise as downscaled PRISM monthly data still involve errors, as shown in Figure 6 and Table I, which affect the precision of estimation for all derived variables. Predictions of the three derived climate variables that did not have a model-fit process including $DD5_{100}$, bFFP, and eFFP turned out to be quite reliable. Especially for $DD5_{100}$, the R^2 was very high (0.95) with a small standard error (4.6). bFFP and eFFP also had a similar or higher precision of predictions compared with FFP (Table II).

3.4. Computer application

We developed an MS Windows software application 'ClimateBC', written in Visual Basic 6.0, that performs all the calculations described here, including bilinear interpolation of PRISM, recent changes in climate means (1998–2002) and regional GCM predictions, elevation adjustment for temperature variables, calculations of derived climate variables, and integration of predicted future climate data into baseline climate variables. The program outputs monthly, seasonal, and annual climate variables for 1961–1990 normals, for the recent past (1998–2002), and for the 2020s, 2050s, or 2080s based on latitude, longitude, and elevation (the latter is optional). It can process a single location through direct input of coordinates in decimal degrees or degrees, minutes, and seconds by the user. Alternatively, multiple locations can be processed through reading an input file comprising coordinates listed in a spreadsheet or a text file. The program is available from the Centre for Forest Gene Conservation at the University of British Columbia: http://genetics.forestry.ubc.ca/cfgc/climate-models.html or from the Research Branch, BC Ministry of Forest, Victoria (to be set up).

3.5. Application example

To illustrate the use of this data, we evaluate the MAT for SPZs of lodgepole pine in British Columbia. SPZs are regions of relatively homogenous climate conditions where forest tree planting stock is deployed for reforestation. Planting stock is matched to planting conditions to avoid maladaptation and ensure optimal productivity. Here, we use a simplified example that compares the average MAT of different SPZs before and after climate change to obtain an approximate idea of the magnitude of impacts on reforestation practices. Mean annual temperature coverages were generated on the basis of a 400-m digital elevation model using the ClimateBC program for the 1961–1990 reference period and the 2020s, 2050s, and 2080s. For this example, we selected the CGCM2-A2x scenario of the Canadian Centre for Climate Modeling and Analysis (Flato *et al*., 2000). Lodgepole pine is planted within two elevation bands within each of these geographic areas. For simplicity, they were averaged in this example, and small overlap zones were omitted.

Maps of lodgepole pine SPZs overlaid to the MATs predicted by the program ClimateBC for current and future years are shown in Figure 9. Average MATs for each SPZ are listed in Table III. Changes in the MAT from current to the future years are substantial. The SPZ Bulkley Valley (BV) in the northwest interior plateau, for example, currently has a MAT of 1.6 °C. However, it is predicted to have a MAT of 2.9 °C in the 2020s, as the current MAT in Nelson (NE, 2.8°) in the southeast interior plateau. In the 2050s, BV is predicted to have a MAT of 4.1 °C, which is higher than the current MATs of all current SPZs. MAT has been found to be one of the most important climate variables driving the adaptation and productivity of lodgepole pine (Rehfeldt *et al*., 2004; Rehfeldt *et al*., 1999). This would imply that the impact on the species and reforestation practices might be drastic if the climate changes as predicted. These high-quality and high-resolution climate variable coverages can now be used to redefine and redelineate current seed zones on the basis of a multivariate characterization of the climate envelop of each and identify suitable future planting environments for seeds originating from different locations. This problem will be addressed in a subsequent paper.

Table III. Mean annual temperatures (°C) of lodgepole pine seed planning zones (SPZs) for the reference period (1961–1990) and predicted for the 2020s, 2050s, and 2080s

SPZ	MAT61–90	MAT2020s	MAT2050s	MAT2080s
Bulkley Valley (BV)	1.6	2.9	4.1	5.5
Central Plateau (CP)	0.5	1.9	3.1	4.5
East Kootenay (EK)	2.1	3.4	4.6	6.0
Nelson (NE)	2.8	4.2	5.4	6.8
Nass Skeena (NS)	2.3	3.7	4.9	6.3
Prince George (PG)	1.9	3.2	4.4	5.8
Peace River (PR)	1.1	2.5	3.8	5.3
Thompson Okanagan (TO)	3.9	5.1	6.3	7.6
Average	2.0	3.4	4.6	6.0

4. CONCLUSIONS

A combination of regression and bilinear smoothing techniques were used to generate scale-free climate normals for monthly temperature and precipitation for western Canada. Normals could then be calculated from latitude, longitude, and elevation. Predictions from the model for an independent set of weather stations agreed well with the measured data. Formulae were derived to calculate monthly normals of derived variables such as DD and frost-free period from the monthly data. These formulae were applied to the scale-free monthly data and again produced values that agreed well with measured data. The format of the data allows for adjustment with climate change scenarios and to be used in impact assessments. The data were used to assess changes in the location of SPZs for lodgepole pine in British Columbia. A stand-alone MS Windows application package was developed to perform all calculations and to integrate future climate predictions from various global circulation models.

As the scale-free prediction is PRISM-based, some of the shortfalls in PRISM data cannot be avoided. For example, poor predictions of PRISM data for areas that are not well covered by weather stations (Hamann and Wang, 2004) could also result in relatively poor scale-free predictions. PRISM data were generated on the basis of data from weather stations recorded at 1.5-m height at open areas. Consequently, scale-free predictions also represent climate at the same circumstance. Thus, care needs to be taken when applying them in resource analysis. The microclimate of small-scale topographic features, e.g. frost pockets and rivers and lakes, will not be correctly represented. Forest canopies are often a few degrees cooler during the day and warmer at night than open areas. Air temperature under a snow pack can be substantially higher than that of the air above the pack. Consequently, as with using individual weather station data, users need to know how the environment of the organism of interest may vary from the reference values generated using the scale-free predictions.

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