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Examination of change factor methodologies for climate change impact assessment

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[1] A variety of methods are available to estimate values of meteorological variables at future times and at spatial scales that are appropriate for local climate change impact assessment. One commonly used method is Change Factor Methodology (CFM), sometimes referred to as delta change factor methodology. Although more sophisticated methods exist, CFM is still widely applicable and used in impact analysis studies. While there are a number of different ways by which change factors (CFs) can be calculated and used to estimate future climate scenarios, there are no clear guidelines available in the literature to decide which methodologies are most suitable for different applications. In this study several categories of CFM (additive versus multiplicative and single versus multiple) for a number of climate variables are compared and contrasted. The study employs several theoretical case studies, as well as a real example from Cannonsville watershed, which supplies water to New York City, USA. Results show that in cases when the frequency distribution of Global Climate Model (GCM) baseline climate is close to the frequency distribution of observed climate, or when the frequency distribution of GCM future climate is close to the frequency distribution of GCM baseline climate, additive and multiplicative single CFMs provide comparable results. Two options to guide the choice of CFM are suggested. The first option is a detailed methodological analysis for choosing the most appropriate CFM. The second option is a default method for use under circumstances in which a detailed methodological analysis is too cumbersome.

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1. Introduction

[2] New York City Department of Environmental Protection (DEP) is undertaking a program to evaluate the potential effects of climate change on the New York City (NYC) water supply. This modeling program utilizes meteorological time series derived from Global Climate Model (GCM) simulations. These time series are provided as input to an integrated suite of models (including watershed hydrology, water quality, water system operations, and reservoir hydrothermal models), to examine the potential effects of climate change on water quantity and quality.

[3] One difficulty encountered in such studies is the mismatch of spatial scales between GCMs on the one hand, and local observations and local impact assessments on the other hand. For example, the area of typical GCM grid cells range between 10,000 km^2 and 90,000 km^2, while for the case of the NYC water supply, model simulations are typically run on watershed areas of 25–1200 km^2.

[4] A number of techniques have been employed to overcome this problem of mismatched spatial scales. Future climate scenarios have been derived in several ways: (1) based on analogies with different climatic zones or historical time periods, (2) from GCMs using simple manipulation of current climate observations (e.g. Change Factor Methodology (CFM)), and (3) from more sophisticated statistical and dynamical downscaling methodologies [*Wilby et al.*, 2000]. There are three types of statistical downscaling, namely weather classification methods, weather generators, and transfer functions. Weather classification methods group days into a finite number of discrete weather types or "states" according to their synoptic similarity [*Anandhi*, 2010; *Brinkmann*, 1999; *Wetterhall et al.*, 2005]. Weather generators are statistical models that provide sequences of weather variables that have similar statistical properties as the observed data on which they are trained [*Chen et al.*, 2010; *Mehrotra et al.*, 2006; *Stehlik and Bárdossy*, 2002; *Wilks*, 1998]. Transfer functions capture the relationships between the large scale atmospheric variables (predictors) and the local meteorological variable of interest (predictand) [*Anandhi et al.*, 2008; *Anandhi et al.*, 2009; *Tripathi et al.*, 2006]. In the dynamic downscaling approach, a Regional Climate Model (RCM) is nested in a GCM. Dynamic

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downscaling can be further subdivided into one-way nesting and two-way nesting [*Wang et al.*, 2004].

[5] Each of the methods has its own set of advantages and pitfalls for generating future climate scenarios [*Mearns et al.*, 2001; *Semadeni-Davies*, 2004]. The major advantage of CFM (also referred to as delta change factor methodology) is the ease and speed of application, and the direct scaling of the local data in line with changes suggested by the GCM scenario. Hence, CFM is used in many climate change impact assessment studies [*Semadeni-Davies et al.*, 2008] and programs across the world, such as the US Global Change Research Program (available at http://www.usgcrp.gov/usgcrp/nacc/default.htm), and in a recent study of the effect of climate change impact on lakes in Europe (CLIME) [*George*, 2010]. However, there are also some disadvantages to this approach that have been reported in the literature. For example, the temporal sequencing of wet and dry days generally remains unchanged when using single change factor (explained in detail in section 3.1), and so CFM may not be helpful in circumstances where changes in event frequency and antecedent conditions are important to the impact assessment [*Diaz-Nieto and Wilby*, 2005; *Gleick*, 1986]. The purpose of this paper is to shed some light on the different types of CFM methodologies under different circumstances, and to provide guidance on how they should be applied.

2. Study Region and Data

[6] Our study region is the Cannonsville reservoir watershed, which is one of the sources of NYC's municipal water supply. Cannonsville is a 1178 km^2 watershed located in Delaware County, about 160 km northwest of NYC in the Catskill Mountains.

[7] Daily GCM simulation results from three GCMs are downloaded for the grid box closest to the centroid of the watershed. The National Center for Atmospheric Research (NCAR), Goddard Institute of Space Studies (GISS), and European Center Hamburg Model (ECHAM) are the three GCMs used in the study. The GCM simulations were obtained from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multimodel data set. The NCAR, GISS, and ECHAM results were supplied by Columbia University/GISS as part of an initial climate change contract with DEP [*Horton and Rosenzweig*, 2010; *Major and O'Grady*, 2010]. The scenarios include a baseline scenario (20C3M), three future emission scenarios (A1B, A2, and B1), and two time slices (2046–2065 and 2081–2100). All combinations of future emissions scenarios and time slices are compared to the 1981–2000 baseline period, and nine meteorological variables were examined depending on their availability (precipitation; maximum, minimum and average temperature; meridional wind component; zonal wind component; surface pressure; shortwave solar radiation; and longwave radiation; as discussed in section 4.3). The temperature and winds are at the near surface, usually 2 m height for temperature and 10 m height for wind. The chosen future scenarios coincide with daily data available for most GCMs. The details of the GCMs used in the study are provided in Table 1.

[8] Daily observed data from six meteorological variables (precipitation; maximum, minimum and average temperature; wind speed; and shortwave solar radiation) for the period 1981–2000 are used in the more detailed study in section 4.4. For these variables, there was no significant change in the frequency distributions calculated over a 20 (1981–2000) or 40 (1961–2000) year record of observed data.

Table 1. GCMs, Emission Scenarios, and Time Slices Applied in This Study[a]

GCM	20C3M	Emission Scenarios	Time Slices
ECHAM	1981–2000	A2, A1B, B1	2046–2065, 2081–2100
GISS	1981–2000	A2, A1B, B1	2046–2065, 2081–2100
NCAR	1980–1999	A2, A1B	2045–2064, 2080–2099

[a]Time slice refers to the interval of time used in the calculation of change factors.

3. Change Factor Methodologies

[9] There are several types of CFMs. These can be categorized by temporal scale, temporal resolution, mathematical formulation, or number of change factors. The first type of CFM is categorized by the temporal scale and temporal domain from which they are calculated. Temporal scale refers to the timescale (e.g. daily, monthly, seasonal, annual) of values that are included in the analysis. Temporal domain refers to both the time of year (e.g. January, winter, annual) and the beginning and ending dates of the historical observed, historical modeled, and future modeled values to be included in the analysis (e.g. 1981–2000 compared to 2046–2065). In general, the reliability of GCMs decrease at higher frequency temporal scales. The monthly, seasonal, and annual averages of any variable are better simulated than daily values [*Grotch and MacCracken*, 1991; *Huth*, 1997]. However, there is also a need for daily hydrometeorological variables in hydrological and ecological impact assessment studies relating to climate change. Studies have evaluated GCM simulations at daily timescales and concluded that some of the GCMs (in AR4 report) show considerable skill at subcontinental scales even when assessed using daily frequency distributions. This builds confidence in using the GCMs for regional assessment [*Perkins et al.*, 2007] and in some cases for assessing extreme events.

[10] The second type of CFM is categorized by its mathematical formulation (additive or multiplicative). In an additive CFM, one calculates the arithmetic difference between a GCM variable derived from a current climate simulation and derived from a future climate scenario taken at the same GCM grid location. This difference is then added to observed local values to obtain the modeled future values. This method, typically used for temperature [*Akhtar et al.*, 2008; *Hay et al.*, 2000; *Kilsby et al.*, 2007], assumes that the GCM produces a reasonable estimate of the *absolute change* in the value of a particular variable regardless of the accuracy of the GCM's current climate simulation. A multiplicative change factor (CF) is similar to an additive CF except that the ratio, rather than arithmetic difference, between the future and current GCM simulations is calculated; the observed values are then multiplied by (rather than added to) the CF. This method assumes that the GCM produces a reasonable estimate of the *relative change* in the value of a variable, and is typically used for precipitation

[*Akhtar et al.*, 2008; *Hay et al.*, 2000; *Kilsby et al.*, 2007]. If CFs are to be applied multiplicatively for temperature values, the Kelvin scale should be used. In some studies change factors are applied incrementally by arbitrary amounts (e.g. +1, +2, +3, +4°C change in temperature). The scenarios obtained are also referred to as synthetic scenarios [*Carter et al.*, 1994], as they do not necessarily present a realistic set of changes that are physically plausible. They are usually adapted for exploring system sensitivity prior to the application of more credible, model-based scenarios [*Rosenzweig and Iglesias*, 1994; *Smith and Hulme*, 1998].

[11] There are no clear guidelines available in the literature as to whether CFs are to be estimated additively or multiplicatively for meteorological variables such as wind speed and solar radiation. Nevertheless, these values are sometimes required for impact assessment studies in hydrology. Hence, there is a need to develop a methodology for applying CFs across a wide variety of meteorological variables.

[12] The third type of CFM is categorized based on the number of change factors (single and multiple CFs). Single CFs are calculated identically for all values of the variable, regardless of magnitude [*Akhtar et al.*, 2008; *Hay et al.*, 2000]. Multiple CFs are those that are calculated separately for different magnitudes of the variable [*Andréasson et al.*, 2004; *Kilsby et al.*, 2007; *Olsson et al.*, 2009]. For example, one can calculate separate CFs for percentiles 0–10, 10–20, and so on for the meteorological parameter of interest. There are no clear guidelines available that suggest the appropriate number of CFs.

[13] For any particular CFM analysis, one must choose CF values that are appropriate for the methodology being applied. As an example of a particular analysis, one might consider a temporal scale of daily; a temporal domain that includes all January values for the time period 1981–2000 compared to 2046–2065; and an additive, single CF. It is likely that one might want to do the analysis for each month of the year. In that case, each monthly analysis would be performed independently. The CFs may be obtained from a single GCM grid point or an average of grid points. In the remainder of this section, calculations of CFs are discussed.

3.1. Single CF

[14] The procedure to calculate a single CF, additively or multiplicatively, is explained in this section and illustrated in Figure 1. The first step is to estimate the mean values of GCM simulated baseline and future climates (equations (1) and (2)).

$$\overline{GCMb} = \sum_{i=1}^{Nb} \boldsymbol{GCMb}_i / Nb \tag{1}$$

$$\overline{GCMf} = \sum_{i=1}^{Nf} \boldsymbol{GCMf}_i / Nf \tag{2}$$

[15] In equations (1) and (2) *GCMb* and *GCMf* represent the values from a GCM baseline (20C3M) and GCM future climate scenario, respectively, for a temporal domain. $\overline{GCMb}$ and $\overline{GCMf}$ are the mean values from a GCM

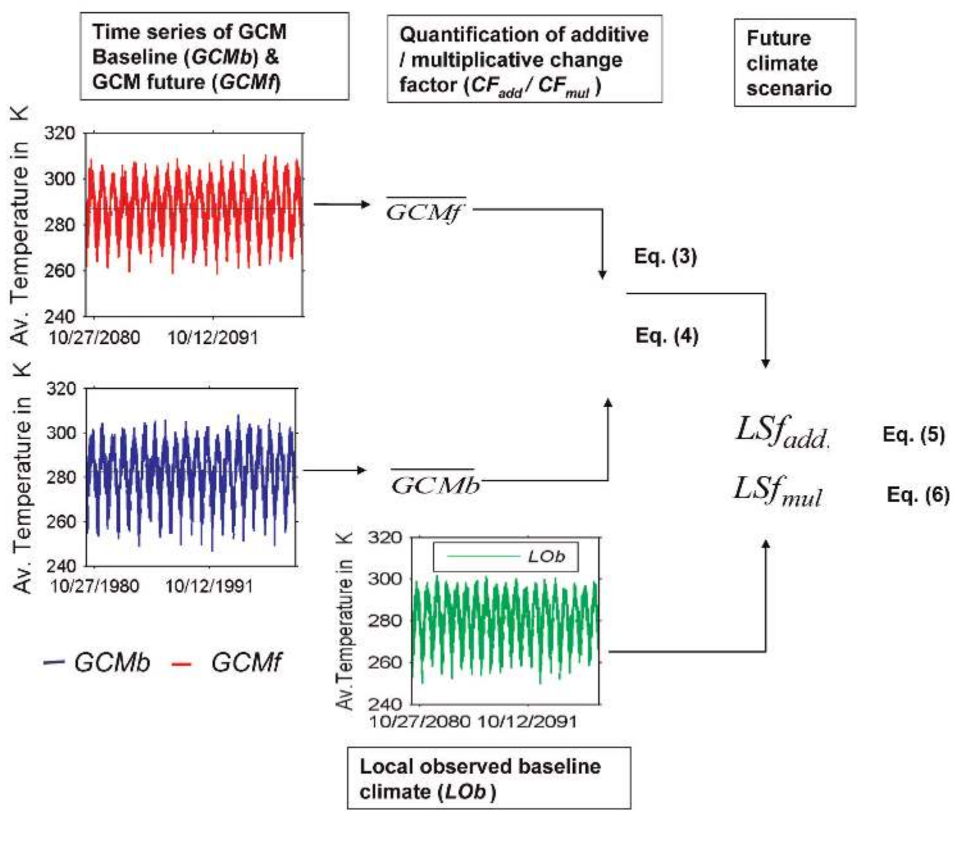

Figure 1. Methodology to estimate future scenarios using "Single additive" and "Single multiplicative" change factors.

baseline and GCM future scenario for the designated temporal domain. Nb and Nf are the number of values in the temporal domain of the GCM baseline and GCM future scenario.

[16] For example, when using a temporal domain corresponding to January 1981–2000, at a daily temporal scale, Nb would be equal to the number of days in all the January months ($Nb = 20 \times 31$) during this time period while for a monthly temporal scale, Nb would be equal to the number of January months ($Nb = 20$). Likewise, for a future temporal domain corresponding to January 2046–2065, at a daily temporal scale, Nf would be equal to the number of days in all the January months ($Nf = 20 \times 31$), and at a monthly temporal scale, Nf would be equal to the number of January months ($Nf = 20$).

[17] Step 2 is to calculate additive and multiplicative change factors (CF_{add}, CF_{mul}) (equations (3) and (4)).

$$CF_{add} = \overline{GCMf} - \overline{GCMb} \tag{3}$$

$$CF_{mul} = GCMf / GCMb \tag{4}$$

[18] Step 3 is to obtain local scaled future values ($\boldsymbol{LSf}_{\mathrm{mul,i}}$ and $\boldsymbol{LSf}_{\mathrm{add,i}}$) by applying CF_{add} and CF_{mul} (equations (5) and (6)).

$$\boldsymbol{LSf}_{add,i} = \boldsymbol{LOb}_i + CF_{add} \tag{5}$$

$$\boldsymbol{LSf}_{mul,i} = \boldsymbol{LOb}_i \times CF_{mul} \tag{6}$$

where $\boldsymbol{LOb}_i$ are observed values of the meteorological variable (at the i^{th} time step) at an individual meteorological station, or are the averaged meteorological time series for a watershed for the designated temporal domain. $\boldsymbol{LSf}_{\mathrm{add,i}}$ and $\boldsymbol{LSf}_{\mathrm{mul,i}}$ are values of future scenarios of the variable obtained using additive and multiplicative formulation of CFM.

3.2. Multiple (Magnitude Dependent) CFs

[19] The procedure to calculate multiple CFs (additively or multiplicatively) is explained in this section. The first step is to estimate the empirical cumulative distribution functions (CDFs) for $GCMf$ and $GCMb$.

[20] Step 2 is to fix the number of bins (n) to be estimated and the resolution of the percentiles (r) in each bin. The bin size may be uniform or nonuniform. In this study the results using six different sets of values for n and r are compared: (1) single CF ($n = 1$, $r = 100$, explained in section 3.1); (2) 3 CFs ($n = 3$, r is variable; 0–25 percentile, 25–75 percentile, and 75–100 percentile); (3) 10 CFs ($n = 10$, $r = 10$); (4) 25 CFs ($n = 25$, $r = 4$); (5) 50 CFs ($n = 50$, $r = 2$); and (6) 100 CFs ($n = 100$, $r = 1$).

[21] Calculations within each bin are analogous to the calculations required for a single CF (section 3.1), so that equations (7)–(12) are analogous to equations (1)–(6), except that the former have subscripts "n" denoting that the calculations are specific for each bin. In step 3, for each bin, mean values $GCMf$ and $GCMb$ are estimated using equations (7) and (8).

$$\overline{GCMb_n} = \sum_{i=1}^{Nb} \boldsymbol{GCMb}_{i,n} / Nb \tag{7}$$

$$\overline{GCMf_n} = \sum_{i=1}^{Nf} \boldsymbol{GCMf}_{i,n} / Nf \tag{8}$$

[22] In step 4, calculate the $CF_{\mathrm{add,n}}$ and $CF_{\mathrm{mul,n}}$ for each bin (equations (9) and (10))

$$CF_{add,n} = \overline{GCMf_n} - \overline{GCMb_n} \tag{9}$$

$$CF_{mul,n} = \overline{GCMf_n} / \overline{GCMb_n} \tag{10}$$

[23] The fifth step is to estimate the CDF for $\boldsymbol{LOb}$, and divide $\boldsymbol{LOb}$ into the same bin and percentile classes as was used with the GCM data.

[24] The final step is to obtain future scaled climate values ($\boldsymbol{LSf}_{\mathrm{mul,n,j}}$ and $\boldsymbol{LSf}_{\mathrm{add,n,j}}$) by applying the change factors to the corresponding observed values (j) in each bin in the baseline period $\boldsymbol{LOb}$ using the general equations (11) and (12).

$$\boldsymbol{LSf}_{add,n,j} = \boldsymbol{LOb}_{n,j} + CF_{add,n} \tag{11}$$

$$\boldsymbol{LSf}_{mul,n,j} = \boldsymbol{LOb}_{n,j} \times CF_{mul,n} \tag{12}$$

4. Results and Discussion

[25] In this section the behaviors of different types of CFMs are demonstrated. In the first two sections, theoretical examples of additive and multiplicative methodologies for single (section 4.1) and multiple (section 4.2) CFs are presented. Then a case study using multiple CFs from real observations (section 4.3) is shown, followed by a comparison of single and multiple CF results (section 4.4). Results of additive and multiplicative categories of CFMs are discussed in sections 4.1 to 4.4.

4.1. Theoretical Example of a Single CF

[26] It is shown, using a theoretical example, how the estimated local scaled future value (LSb) depends on (1) the choice of additive or multiplicative CFM; (2) the magnitude of the bias in the baseline period between local observed climate ($\boldsymbol{LOb}$) and GCM baseline climate ($\overline{GCMb}$); and (3) the magnitude of the change factor. In the example, the local observed value ($\boldsymbol{LOb}$) of exactly 1 is assumed. We then estimate the local scaled future climate ($\boldsymbol{LSf}_{\mathrm{add}}$ and $\boldsymbol{LSf}_{\mathrm{mul}}$) using both additive and multiplicative CFs based on a range of values for GCM baseline climate ($\overline{GCMb}$; x axis in Figure 2) and GCM future climate ($\overline{GCMf}$; y axis in Figure 2). The differences (D) between the $\boldsymbol{LSf}_{\mathrm{add}}$ and $\boldsymbol{LSf}_{\mathrm{mul}}$ obtained additively and multiplicatively, calculated using equation (13), are shown as contours in Figure 2.

$$\boldsymbol{D} = \boldsymbol{LSf}_{\boldsymbol{mul}} - \boldsymbol{LSf}_{\boldsymbol{add}} \tag{13}$$

[27] This example can apply to a single CF, or to a particular bin in a multiple CF. The results shown in Figure 2 demonstrate that when the frequency distribution of GCM baseline simulation is close to the frequency distribution of observed baseline climate (i.e., small bias) or when the

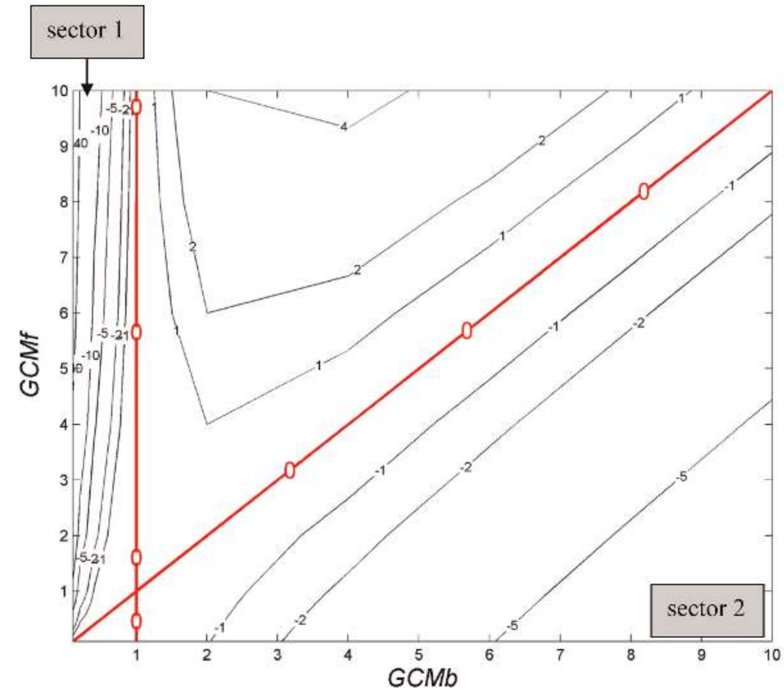

Figure 2. The contour plot of the differences in future scenario values obtained from additive and multiplicative change factors is calculated using equation (13), from the theoretical values of GCM baseline mean ($\overline{GCMb}$, x axis) and GCM future mean ($\overline{GCMf}$, y axis). A local observed baseline (***LOb***) value of exactly 1 is assumed. The 0 contours following the diagonal line represent small bias while those following the vertical line represent small change factors as explained in section 4.1. Contours are not equally spaced. Sectors 1 and 2 are referred to in section 4.4.

mean GCM baseline is close to the mean GCM future simulations (i.e., small change factor), there is little difference between the additive and multiplicative methods. These are areas with a value near 0 (represented in Figure 2 as bold red lines). However, as the bias in the baseline GCM simulation increases, or as the absolute value of the change factor gets larger, the additive and multiplicative methods produce more and more divergent results.

4.2. Theoretical Example of a Multiple CFM

[28] A graphical approach is developed to evaluate multiple CFMs using "difference plots" and "ratio plots," which are defined here. In this example, CFs are calculated for 100 bins of equal width (i.e., all widths span exactly 1 percentile) using both additive and multiplicative methods (Figure 3). CF values are on the abscissa axis, and percentile values are shown on the ordinate axis. This example shows the simple case where, for all bins, the difference between the current and future climates modeled by the GCM is a constant value. In other words, the additive CF is independent of the magnitude of the values. In such a case, the difference plot is a straight vertical line, and the ratio plot is a curved line.

[29] Figures 3 and 4 show more generally how the difference and ratio plots look for the simple cases where, across bins, there is a constant difference or constant ratio between current and future climates. These plots can be considered theoretical templates against which to compare similar plots derived from GCM output, and which may be useful in determining whether an additive or multiplicative method is most appropriate. However, it is demonstrated in section 4.3, that results from GCM experiments are unlikely to be as simple or as obvious as the theoretical example shown in Figures 3 and 4.

4.3. Real Example of a Multiple CFM

[30] A real example from the Cannonsville watershed (see section 2) is shown in Figure 5. Difference plots and ratio plots were derived using daily values from three GCMs (NCAR, ECHAM, and GISS), three emission scenarios (A1B, A2, and B1), and two time slices (2046–2065 and 2081–2100, both of which are compared to the 1981–2000 baseline period). Nine meteorological variables (precipitation; maximum, minimum, and average temperature; meridional wind component; zonal wind component; surface pressure; wind speed; shortwave solar radiation; and longwave solar radiation) were examined. From all of these combinations of meteorological variables, time periods, and emission scenarios, a variety of patterns in the ratio and difference plots were observed. Figure 5 shows a selection of difference and ratio plots that are considered illustrative of more general results.

[31] The difference and ratio plots for our study area can be broadly classified into five groups. The five classifications include those in which: (1) the difference plot is close to a straight vertical line, indicating that a single additive CF is appropriate (Figure 5a); (2) the ratio plot is close to a straight vertical line, indicating that a single multiplicative CF is appropriate (Figure 5b); (3) the difference plot is close to multiple straight vertical lines for different percentile

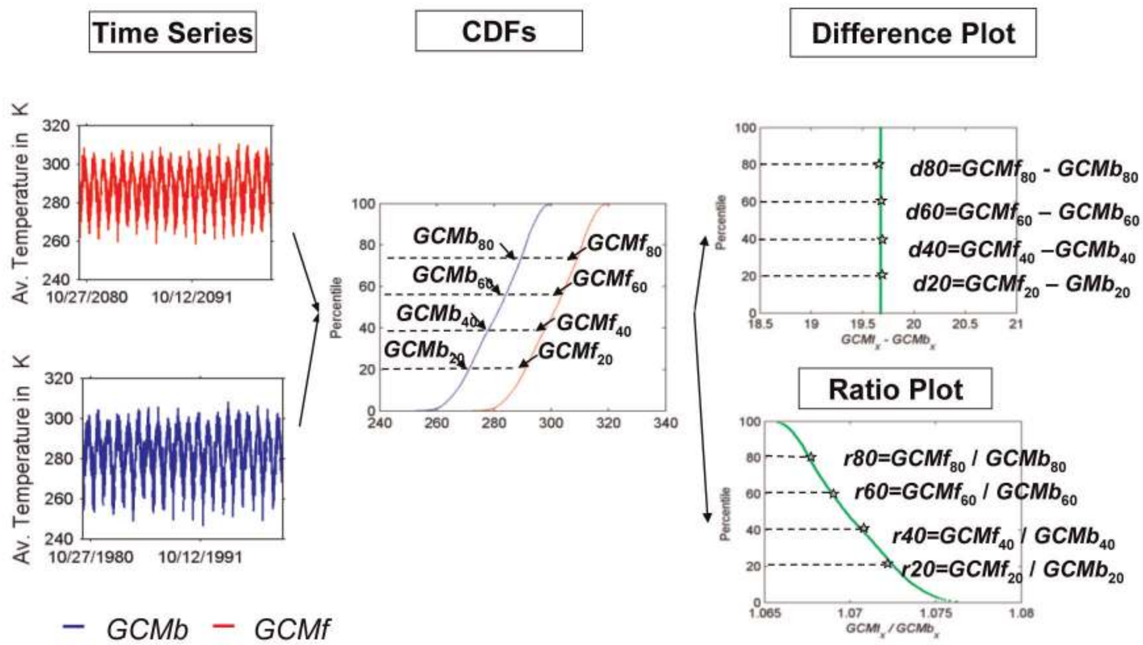

Figure 3. Explains the procedure used to obtain difference plot and ratio plots for use in the graphical approach to study the distribution of the CFs in different magnitudes of the variable. The calculations associated with 4 specific percentiles are illustrated using dashed lines. The difference plot and ratio plot shown in the figure are theoretical templates to guide the choice of change factor methodology (CFM) in cases where an additive CF is appropriate in which case the difference plot will be a vertical line and the ratio plot will be a curved line.

ranges (say 1st through 50th percentiles, 50th through 100th percentiles), indicating that multiple additive CFs are appropriate (Figure 5c); (4) the ratio plot is close to multiple straight vertical lines for different percentile ranges (say 1st through 50th percentiles, 50th through 100th percentiles), indicating that multiple multiplicative CFs are appropriate (Figure 5d); and (5) both the difference and ratio plots are curved, indicating a larger number of multiple multiplicative or additive CFs are probably in order (Figure 5e).

[32] It is found that the shapes of the difference and ratio plots vary depending on meteorological variables, GCMs,

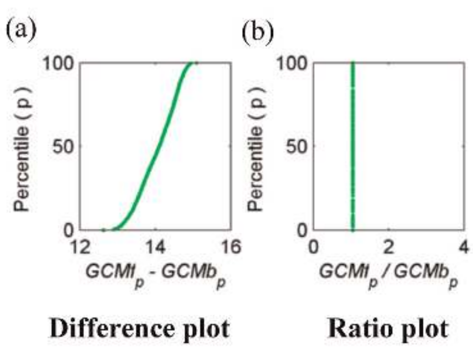

Figure 4. Theoretical templates of difference and ratio plots to guide the choice of change factor methodology (CFM). In cases where a multiplicative CF is appropriate, (a) the difference plot will be a curved line and (b) the ratio plot will be a vertical line.

and special report on emission scenarios (SRES) scenarios. Hence, we infer that fixing a single type of CF formulation for use in this region may not be appropriate. We assume that this type of variability in CFs is probably the norm, not the exception. Thus, to apply this methodological analysis for multiple variables/GCMs in a particular region may in many cases be quite cumbersome. This raises the question of how to proceed in such a case, and whether there is a method that can be applied more generally that would circumvent the need for such a cumbersome analysis. This is addressed in section 4.4.

4.4. Comparison of Single and Multiple CF Results

[33] In this section we determine whether one particular method is generally as good as, or better than, the others in all or most circumstances. Using six of the nine meteorological variables (the only ones for which observations were available at this location), both additive and multiplicative CFs were used to estimated future climates either as a single CF or from multiple CFs using 3, 10, 25, 50, and 100 bins. This results in six $\boldsymbol{LSf}$ time series derived using the additive method, as well as six $\boldsymbol{LSf}$ time series derived using the multiplicative method, for each GCM, emission scenario, and future time period.

[34] For each future scenario, the root mean sum of squares of the differences (RMSD, defined in equation (14)) between the additive and multiplicative $\boldsymbol{LSf}$ series are calculated for all bin sizes.

$$RMSD = \sqrt{\sum (\boldsymbol{LSf}_{mul} - \boldsymbol{LSf}_{add})^2} \qquad (14)$$

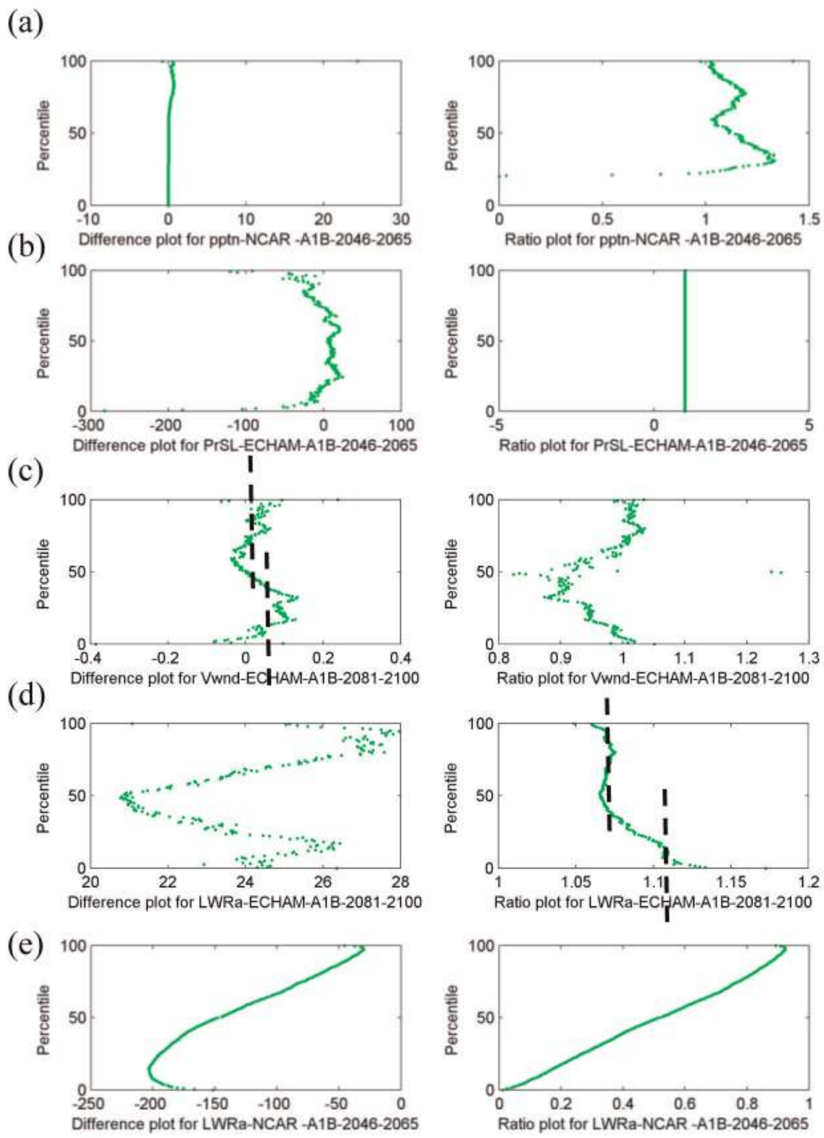

Figure 5. Illustrative examples of difference and ratio plots from a study of the Cannonsville basin. (a) Single additive CFM, where the difference plot is close to a straight vertical line and ratio plot is curved. (b) Single multiplicative CFM, where the ratio plot that is close to a straight vertical line and difference plots is curved. (c) Multiple additive CFM, where the difference plot is close to multiple straight vertical lines within different percentile bands (i.e., 1st through 40th percentiles, 40th through 100th percentiles) and the ratio plot is curved. (d) Multiple multiplicative CFM, where the ratio plot is close to multiple straight vertical lines for different percentile bands (i.e., First through 25th percentiles, 25th through 100th percentiles) and the difference plot is curved. (e) Nondefinitive CFM, where the difference plots and ratio plots are both curved. Pptn, PrSL, Vwnd, LWRa in the panel abscissa titles refer to precipitation, sea level pressure, meridional wind and longwave radiation respectively.

[35] Figure 6 shows how RMSD depends on bin size for one sample scenario (SRES A2). As the number of bins is increased, RMSD always stabilizes to a constant value. Stabilization of values occurs as the number of bins exceeds approximately 25. Furthermore, in most cases RMSD is also minimized with $>=25$ bins. In some cases RMSD increases with increasing bin size (in the example shown in Figure 6, shortwave radiation for the GISS model). This is because the projected change is large, falling within either the upper left quadrant (sector 1) or lower right quadrant (sector 2) of Figure 2. The multiplicative CFs $\left(\overline{GCMf}\big/\overline{GCMb}\right)$ in sector 1 are very high, when the value of $\overline{GCMb}$ is very small when compared to $\overline{GCMf}$. Such large CFs result in very unrealistic scenarios. Hence additive CFs was recommended. Further, from the difference and ratio plots obtained derived using daily values from three GCMs (section 4.3), it was inferred that fixing a single CF formulation for use in this region may not be appropriate. It may be noted the RMSD values for temperatures and wind speed are very small of the order of 10^{-4} to 10^{-3} K and 10^{-2} m/sec respectively.

[36] Some meteorological variables have upper and/or lower limits of the value they can have. For example,

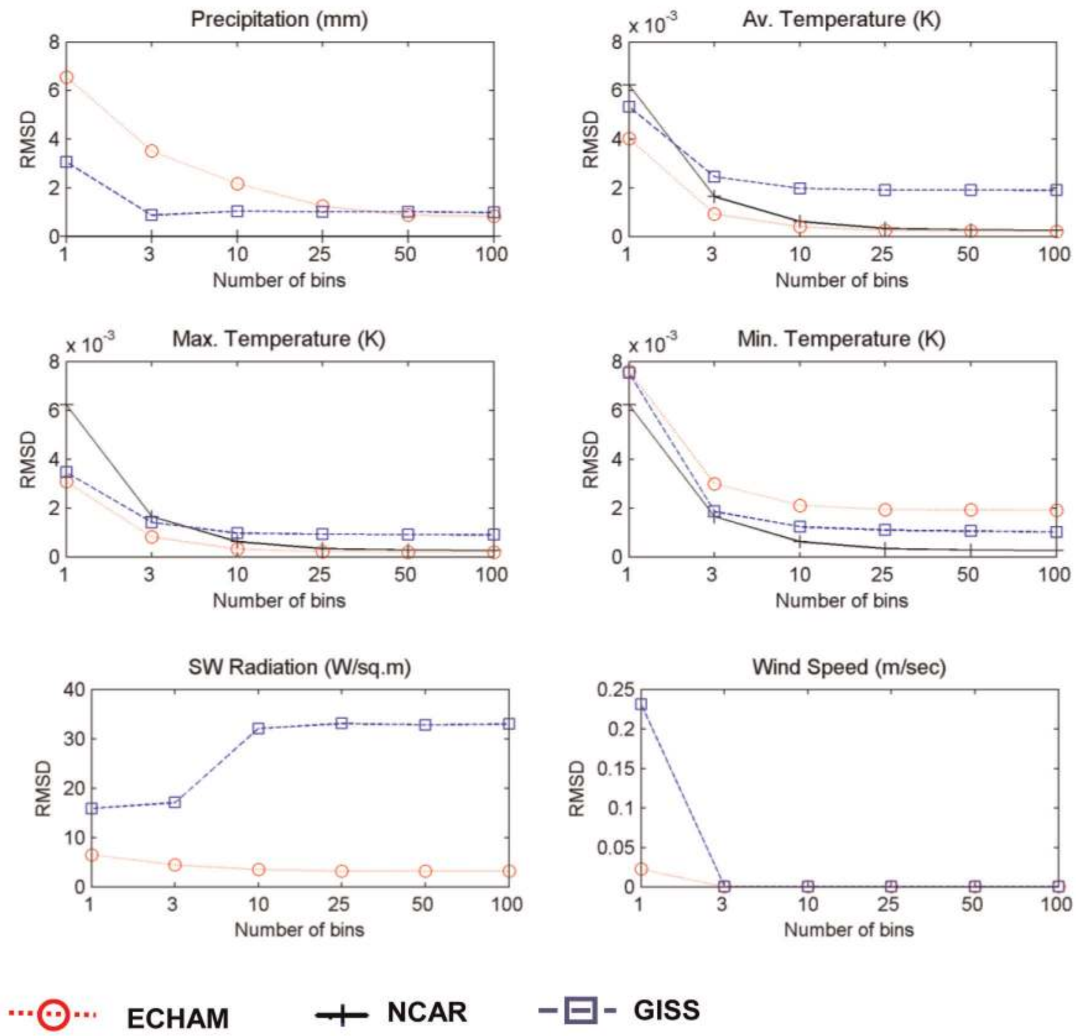

Figure 6. Effect of the number of bins (n) on the difference between additive and multiplicative change factors. On each panel the abscissa shows the number of bins. The ordinate shows the root sum squares of differences (RMSD, equation (14)) between an additive and multiplicative CF. Results taken from three GCMs; A2 emission scenario; base temporal domain is 1981–2000 (January only); future temporal domain is 2046–2065 (January only); six meteorological variables; and daily temporal resolution. In all cases, results stabilize with ≥25 bins. In all cases except GISS shortwave radiation, RMSD is minimized with ≥25 bins.

precipitation and wind speed have a lower limit of 0 (i.e., positive values only). Surface temperatures in absolute scale have a theoretical lower limit (−273 K), but not realistic, so it can be assumed as not having upper and lower limits because such lower temperatures are not plausible. Solar radiation at the earth's surface has a lower limit of 0, and an upper limit equal to the top-of-the-atmosphere radiation multiplied by the maximum transmissivity of the atmosphere (these values vary with latitude and time of year). For variables such as precipitation, wind speed, and solar radiation, the *GCMf* or *GCMb* can have values equal or close to 0, causing multiplicative CFs to be either undefined, or unrealistically high or low.

[37] Thus, there are two main results demonstrated in this section. The first result is that the use of multiple bins usually eliminates the difference between additive and multiplicative CFs. This is because with multiple CFs, the magnitude of the CF in any bin (i.e., for any magnitude of the variable) is independent of the magnitude of CFs in other bins. Thus, multiple CFs can mimic single CFs (when the magnitudes of the CFs for different variable values are dependent on each other) as well as more complicated cases (when the magnitudes of the CFs for different variable values are completely independent). Single CFs can essentially be considered a special case of multiple CFs. Furthermore, when using a sufficient number of bins (25 or more in our analysis) the differences between additive and multiplicative CFs are eliminated.

[38] The second main result is that additive CFs are preferable to multiplicative CFs. This is because of the problem that multiplicative CFs encounter with undefined, or unrealistically small or large, CFs associated with variable

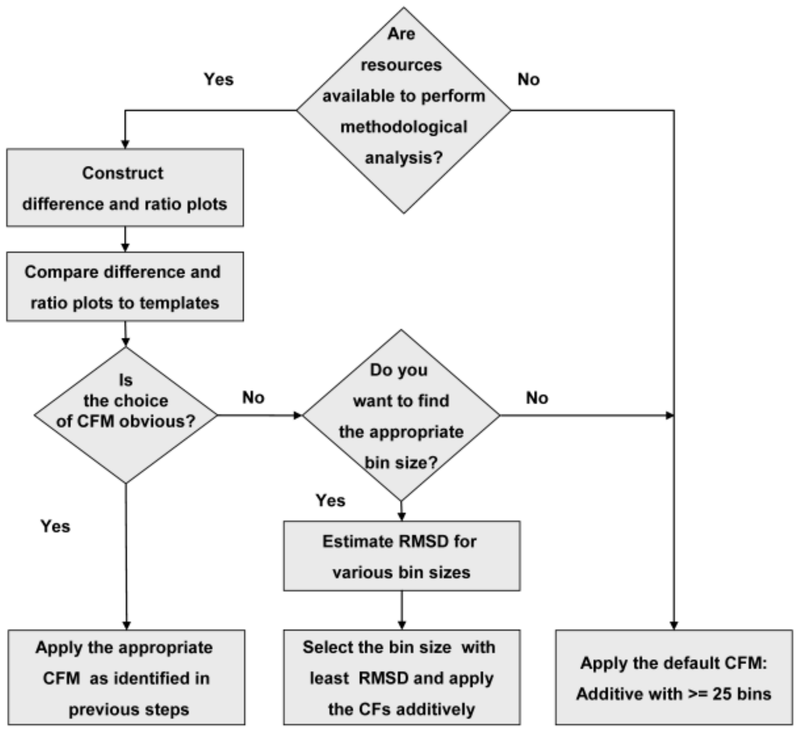

Figure 7. Flowchart of the procedure developed in this study to determine the appropriate type of CFM to be used for a particular variable, location, GCM and scenario. The symbols CFM, CF and RMSD refer to Change factor methodology, change factor and root mean sum of differences respectively.

values near 0. Additive CFs avoid such problems. While using additive CFs, the values of future meteorological variables which have a 0 lower limit should be checked to make sure that they do not get negative values (e.g. precipitation, wind speed, solar radiation).

5. Summary and Conclusions

[39] In this study we compare and contrast different categories of Change Factor Methodology (CFM) when using GCM results to project future climate for subgrid-scale impact analyzes. For some variables, the choice of additive versus multiplicative seems, as inferred by their general usage in the published literature, to be intuitive to researchers (e.g. additive for temperature, multiplicative for precipitation) although the physical reasoning behind these choices has not been adequately explained and is not obvious. For other variables (e.g. wind speed) there seems to be little or no precedent in the literature.

[40] In cases when the frequency distribution of GCM baseline climate is close to the frequency distribution of observed climate (i.e., the GCM climate simulation has a small bias), or when the frequency distribution of GCM future climate is close to the frequency distribution of GCM baseline climate (i.e., the GCM projects only a small climate change), additive and multiplicative single CFMs provide comparable results. However, the greater the difference between modeled and observed baseline climates, or the greater the projected climate change, the greater will be the difference in the local climate change projections made by these two methods. In general, multiple CFMs provide local climate change projections that are more consistent between the additive and multiplicative methods.

[41] This study suggests two options to guide the choice of change factor methodology: (1) In studies where a detailed methodological analysis is possible, the difference and ratio plots introduced in this study may be useful in determining whether an additive or multiplicative method is most appropriate. Our suggested steps for performing such an analysis are discussed in the results section and outlined in Figure 7. (2) In most circumstances, however, it is likely to be too cumbersome to perform such a detailed study for each of the different locations, GCMs, scenarios, and variables needed in a climate change impact analysis. Also, in many cases the difference and ratio plots may not provide conclusive evidence as to which type of CFM to employ. In all circumstances in which a detailed methodological analysis cannot be performed, or the choice of CFM is not obvious, we recommend that multiple additive CFs with $\geq$25 bins be used. This will minimize the impact of the choice of whether to use the additive or multiplicative method, and remove one source of uncertainty from the analysis.

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