Lake Champlain Basin SWAT Climate Response Modeling

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This report was prepared for the U.S. Environmental Protection Agency (EPA) Region 1, in support of activities pursuant to the revision of the Lake Champlain Phosphorus total maximum daily load (TMDL). Multiple objectives were addressed under the scope of the overall project, including revising and recalibrating the lake model used to develop the original TMDL and linking it to a Soil and Water Assessment Tool (SWAT) watershed model to characterize loading conditions and sources in the watershed and estimate potential for loading reductions in the Vermont portions of the basin. A specific objective of the SWAT watershed model was to facilitate the analysis of the impacts of climate change to phosphorus loading in the watershed. This report presents the results of that analysis. Response to future possible climates was evaluated for the Lake Champlain basin for the 2040-2070 time horizon. A total of 6 climate scenarios were examined, as described below. Details related to the calibrated SWAT model are available in the final model calibration report (Tetra Tech 2013).

The model runs for the climate change analysis were completed in 2013 using baseline P, sediment, and flow estimates generated by SWAT for the Lake Champlain basin in 2013. The baseline flow and load estimates have subsequently been revised based on 2014 updates to the TMDL SWAT modeling analysis. The climate change analyses described in this report do not take into account the updated baseline estimates. However, the main purpose of the climate change analysis was to understand the percent change projected for these parameters by mid-century. The percent change values are expected to be almost identical for both sets of baseline data, so the climate change projections have not been re-run with the new baseline data due to resource limitations.

Climate Scenarios

The scientific uncertainties related to our understanding of the physical climate system are large, and they will continue to be large for the foreseeable future. It is beyond our current capabilities to predict with accuracy decadal (and longer) climate changes at the regional spatial scales of relevance for watershed processes (e.g., see Cox and Stephenson, 2007; Stainforth et al., 2007; Raisanen, 2007; Hawkins and Sutton, 2009; among many others). The uncertainties associated with socioeconomic trajectories, technological advances, and regulatory changes that will drive greenhouse gas emissions changes (and land use changes) are even larger and less potentially tractable.

Faced with this uncertainty, an appropriate strategy is to take a scenario-based approach to the problem of understanding climate change impacts on water quality. A scenario is a coherent, internally consistent, plausible description of a possible future state of the world. Scenarios are used in assessments to provide alternative views of future conditions considered likely to influence a given system or activity. By systematically exploring the implications of a wide range of plausible alternative futures, or scenarios, we can reveal where the greatest vulnerabilities lie. This information can be used by decision makers to help understand and guide the development of response strategies for managing climate risk. A critical step in this approach is to create a number of plausible future states that span the key uncertainties in the problem. The goal is not to estimate a single, "most likely" future trajectory for each study watershed, but instead to understand, to the extent feasible, how big an envelope of potential future impacts we are unable to discount and must therefore incorporate into future planning.

A fundamental issue in interpreting Global Climate Models (GCMs) to watershed impacts is that the global models predict climate at a large spatial scale (approximately 200x200 km) and ignore many details of local topography that influence rainfall and temperature. This scale is too coarse for analyzing watershed response; therefore it is necessary to develop refined local estimates of future climate through the process of "downscaling." This can be done in several ways, including dynamical downscaling, in which regional climate models (RCMs) are forced with the GCM climate output scenario, and through a variety of statistical methods, both of which are intended to develop more reliable local climate forecasts.

In practice, when relying on models to develop climate scenarios, the ensemble approach means sampling across multiple GCMs, multiple methodologies for downscaling the model output to finer scales, and, depending on the time horizon considered, multiple greenhouse gas pathways. Use of a single model run is not considered scientifically rigorous for climate impacts studies. This is because, while the leading GCMs often produce very different results for future climate change in a given region, there is no consensus in the climate sciences communities that any of these are across-the-board better or more accurate than the others (e.g., see Gleckler et al. 2008).

NARCCAP (2040-2070)

EPA provided data for six regionally downscaled climate change scenarios (based on four underlying GCMs) acquired from the National Center for Atmospheric Research (NCAR) North American Regional Climate Change Assessment Program (NARCCAP) project (representative of the future period 2040-2070) (Mearns 2009; http://www.narccap.ucar.edu). The NARCCAP program uses a variety of different RCMs to downscale the output from a few of the Intergovernmental Panel on Climate Change (IPCC) GCMs to higher resolution over the conterminous United States and most of the rest of North America. NARCCAP's purpose is to provide detailed scenarios of regional climate change over the continent, while, by employing the RCMs and GCMs in different combinations, systematically investigating the effect of modeling uncertainties on the scenario results (i.e., uncertainties associated with using different GCMs, RCMs, model physical parameterizations and configurations). The downscaled output is archived for the periods 1970-2000 and 2040-2070 at a temporal resolution of three hours.

NARCCAP uses the IPCC's A2 greenhouse gas storyline, which is a relatively "pessimistic" future greenhouse gas trajectory, represents a continuously increasing global population, regionally oriented economic development, and relatively moderate and fragmented per capita economic growth and technological change. Use of a single greenhouse gas storyline is reasonable in this case where the focus is on a mid-century future period, as the different IPCC greenhouse gas storylines have not yet diverged much by this point, and model uncertainty is therefore correspondingly more important.

Summary of Climate Scenarios

Table 1 shows the specific climate scenarios evaluated. The table also contains a numbering key for shorthand reference to climate scenarios. For example, climate scenario 2 may be seen to refer to the HadCM3 GCM, downscaled with the HRM3 RCM. The matrix of available GCM-downscaling combinations evaluated is shown in another way in Table 2.

Table 1. Specific Climate Scenarios Evaluated

NAARCAP Scenario #	Climate Model(s)
1	CRCM_CGCM3
2	HRM3_HadCM3
3	RCM3_GFDL
4	GFDL high res_GFDL
5	RCM3_CGCM3
6	WRFP_CCSM

Table 2. Matrix of GCMs and Downscaling Approaches Evaluated

	GCM			
	CGCM3	**HadCM3**	**GFDL**	**CCSM**
Downscaling Method/RCM	CRCM (1)	HRM3 (2)	RCM3 (3)	WRFP (6)
	RCM3 (5)		GFDL high res (4)	
	None (7)	None (8)	None (9)	None (10)
	Statistical (11)	Statistical (12)	Statistical (13)	Statistical (14)

Data Processing for Climate Scenarios

The 50-km NARCCAP scale is still too coarse for watershed modeling. There are also known problems in the ability of climate models to predict discrete rainfall events. Therefore, meteorological time series for input to the watershed models were created using a "change factor" or "delta" method. As developed for the GCRP protocol (Johnson et al., 2011), the general strategy for developing meteorological change scenarios appropriate for input to the watershed models from the climate change scenarios is to take approximately 30-year time series of observed local climate observations (to which the watershed models have been calibrated) and perturb these observed data to reflect the change in climate as simulated by the global and regional climate models (and downscaling approaches). The perturbations are based on statistical summaries of change for the different climate scenarios, by month, as calculated from the differences between the 1971-2000 and 2040-2070 climate model simulation periods. These change statistics were used to perturb the existing climate records of precipitation and temperature using the Climate Assessment Tool (CAT), developed under another GCRP effort for EPA's BASINS system[1] (USEPA 2009c). Changes in additional meteorological variables (e.g., solar radiation, relative humidity, wind) are represented by modifying the monthly parameters of the SWAT statistical weather generator.

The base weather data for simulation relies on the 2006 Meteorological Database in EPA's BASINS system, which contains records for 16,000 stations for 1970-2006, set up on an hourly basis. Use of this system has the advantage of providing a consistent set of parameters with missing records filled and daily records disaggregated to an hourly time step. Whereas, a site-specific watershed project would typically assemble additional weather data sources to address under-represented areas, use of the BASINS 2006 data is sufficient to produce reasonable results of the relative magnitudes of potential future change at the broad spatial scales and wide geographic coverage of this project.

[1] http://www.epa.gov/waterscience/basins/

The parameters requested from NARCCAP for the dynamically downscaled model runs were:

- Total precipitation change (mm/day and percent)
- Total accumulated precipitation data for five different percentile bins - 0-25, 25-50, 50-75, 75-90, and greater than 90 percent.
- Surface air temperature, average, daily maximum, and daily minimum (°K and percent)
- Dew point temperature change (°K and percent)
- Relative humidity change
- Surface downwelling shortwave radiation change (W m^{-2} and percent)
- 10-meter wind speed change (m s^{-1} and percent)

The cited statistics were provided for locations corresponding to each of the BASINS meteorological stations and SWAT weather generator stations used in the watershed models. The full suite of statistics is not available for the statistically downscaled model runs or the raw GCM archives. Data availability is summarized in Table 3.

Table 3. Matrix of Available Climate Data for Scenarios

Scenario #	RCM	GCM	Temp.	Prec.	Dew Point Temp	Solar Radiation	Wind Speed	Min Temp.	Max Temp.	Prec. Bin Data
NARCCAP RCM-downscaled scenarios										
1	CRCM	CGCM3	X	X	X	X	X	X	X	X
2	HRM3	HadCM3	X	X	X	X	X	X	X	X
3	RCM3	GFDL	X	X	X	X	X	X	X	X
4	GFDL high res	GFDL	X	X	X	X	X	X	X	X
5	RCM3	CGCM3	X	X	X	n/a	X	X	X	X
6	WRFP	CCSM	X	X	X	X	X	X	X	X

Temperature Implementation

Implementation of future temperature is straightforward. Monthly variations (deltas) to the temperature time-series throughout the entire time-period were applied using the CAT tool. Monthly adjustments based on each scenario were used and a modified HSPF binary data (WDM) file was created. The time-series adjustment to the temperature was adjusted based on an additive change using the deltas (deg K) provided from NARCCAP. An automated script then creates the SWAT observed temperature files (daily maximum and daily minimum).

Precipitation Implementation

The downscaled climate model outputs do not directly provide usable time series of precipitation, as they tend to overestimate the frequency of small events. Instead of using climate model output directly, changes to the existing observed precipitation time series were made based on the relative difference between current and future conditions predicted by the climate models.

A critical issue that was considered is that watershed response depends not only on the volume of precipitation, but also on its timing and intensity. More intense precipitation may be expected to contribute a greater fraction to direct runoff and may also cause a non-linear increase in sediment erosion and pollutant loading. It is anticipated that future climate change will result in intensification of rainfall for some, if not many, regions and seasons (Kundzewicz et al. 2007). The potential intensification (or, where appropriate, de-intensification) is accomplished by partitioning the monthly change statistics into relative changes in the upper 30 percent and lower 70 percent of rainfall event volumes, and modifying the existing time series while maintaining a mass balance as described below. No modifications were made to the number of rainfall events in acknowledgment of the well-recognized fact that climate models tend to predict too many trace rainfall events.

Comprehensive data from NARCCAP (all stations, all climate scenarios) consisting of total predicted precipitation volume (over 30 years) and various percentiles of the 3-hr intensity distribution, by month (valid data were provided for the 0-25, 25-50, 50-70, and 70-90, and >90 percentile bins relative to the existing intensity distribution) were made available. These intensity percentiles yield information on where precipitation intensification occurs, but they are not based on event volumes. The CAT tool (USEPA, 2009b) represents intensification based on events in specific volume classes. It has the ability to specify a constant multiplier to values within a user-specified event size class.

The percentile bin-intensity data were available only for climate scenarios W1 though W6 (RCM-downscaled scenarios). Bin data were not available for scenarios W7 through W14 (GCM and statistically downscaled scenarios). Two approaches were developed to account for intensification of precipitation using the available data: 1) precipitation bin data are available and 2) precipitation bin data are not available. Each approach is discussed in more detail below.

Approach 1: Precipitation Bin Data are Available

This approach is applicable to scenarios 1 through 6 for which the total accumulated precipitation data for different percentile bins (for each station by month) were provided by NARCCAP. Analysis of the comprehensive (percentile, total volume) climate scenario data showed that for most weather stations, the change in the lower percentiles of the intensity distribution appeared to be relatively small compared to the changes above the 70th percentile.

First consider the representation of intensification of larger events. For this the change in the volume about the 70th percentile intensity can be taken as an *index* of the change in the top 30 percent of events. The change in the top 30 percent was selected based on the information on the percentile values of the 3-hr events. At the same time, it is necessary to honor the data on the relative change in total volume. This can be done as shown below. Let the ratio of total volume in a climate scenario (V_2) relative to the baseline scenario volume (V_1) be given by r (V_2/V_1). Further assume that the total event volume (V) can be decomposed into the top 30 percent (V_H) and bottom 70 percent (V_L). These may be related by a ratio $s = V_H/V_L$. To conserve the total volume we must have

$$V_2 = rV_1 .$$

This can be rewritten to account for intensification of the top 30 percent of events as

$$V_2 = rV_{L,1} + rV_{H,1} + rqV_{H,1} - rqV_{H,1} = \left[rV_{L,1} - rqV_{H,1}\right] + \left[r(1+q)V_{H,1}\right],$$

where the first term in brackets at the right represents the total change in the volume of the lower 70 percent of events and the right term represents the total change in the top 30 percent. Substituting for the first $V_{H,1} = s\ V_{L,1}$ yields:

$$V_2 = (r - rqs)V_{L,1} + (r + qr)V_{H.1} .$$

Here again the first term represents the change in the low range of events and the second term the change in the high range. This provides multiplicative factors that can be applied to event ranges using CAT's built-in capabilities on a month-by-month basis.

Next, q can be calculated by defining it relative to the lower 70 percentile values (i.e., from 0 to 70th percentile). Specifically (r-rqs) which represents the events below the 70th percentile can be written as the ratio of the sum of the volumes below the 70th percentile in a climate scenario relative to the sum of the volumes below the 70th percentile for the current condition:

$$r(1-qs) = \frac{(V_{70})_2}{(V_{70})_1} \approx \frac{(Q_{70})_2}{(Q_{70})_1}$$

where $(Q_{70})_1$ and $(Q_{70})_2$ are the sum of the volumes reported up to the 70th percentile for a month for the current condition and future condition respectively.

Again solving the above equation for q yields:

$$q = (1 - A/r)/s$$

where A is defined as $A = \frac{(Q_{70})_2}{(Q_{70})_1}$

In sum, for each month at each station the following were calculated:

$r = {}^{V_2}\!/_{V_1}$ from the summary of the climate scenario output,

$s = {}^{V_H}\!/_{(V - V_H)}$ from the existing observed precipitation data for the station, sorted into events and post-processed to evaluate the top 30 percent (V_H) and bottom 70 percent (V_L) event volumes.

The numerator is calculated as the difference between total volume and the top 30 percent volume, rather than directly from V_L to correct for analyses in which some scattered precipitation is not included within defined "events." The *s* value was calculated by month and percentile (for every station, every month) using the observed precipitation time-series data because this information cannot be reliably inferred from the percentile bin output as it does not reflect the distribution of actual event volumes for the CAT adjustments to preserve the relative volume changes predicted by the climate scenarios.

$q = (1 - A/r)/s$ from the summary of the percentile bin climate scenario output summary

The multiplicative adjustment factors can then be assembled as:

$r\,(1 - qs)$, for the events below the 70th percentile, and

$r\,(1 + q)$, for the events above the 70th percentile.

This approach is also sufficient for the cases where there is a relative increase in the low-percentile. Here the change in the 70th percentile intensity is relatively small and tends to be less than current conditions under the future scenario, resulting in *q* being a small negative number. Then, application of the method results in a decrease in the fraction of the total volume belonging to the larger events, with a shift to the smaller events – thus approximating observed increases in intensity for smaller events.

In general, it is necessary to have $-1 < q < 1/s$ to prevent negative solutions to the multipliers. The condition that $q < 1/s$ is guaranteed to be met by the definition of *q* (because A/r is always positive); however, the lower bound condition is not guaranteed to be met. Further, the calculation of *q* from the percentile bin data is at best an approximation of the actual intensification pattern. To address this problem a further constraint is placed on *q* requiring that some precipitation must remain in both the high and low ranges after adjustment: $-0.8 < q < 0.8/s$. It should be noted that the cases in which negative solutions arose were rare and mainly occurred for stations located in Arizona in the summer months.

Approach 2: Precipitation Bin Data not Available

This approach is applicable for scenarios 7 through 14, for which precipitation bin-intensity data were not available. For all these scenarios it was assumed that all increases in precipitation occur in the top 30 percent of events. In the cases where there was a decline in precipitation for a given month, the decreases were applied across all events.

For the case when $r = V_2/V_1 > 1$ (increasing precipitation), the future volume representing the climate scenario (V_2) can be defined as:

$$V_2 = V_{1L} + r^* \cdot V_{1H},$$

where r^* is the change applied only to the upper range (>30%), V_H is the volume in the top 30 percent, and V_L is the volume in the bottom 70 percent of events.

Setting $r^* = r + (r-1) \cdot V_{1L}/V_{1H}$, the overall change is satisfied, as:

$$V_2 = V_{1L} + r^* \cdot V_{1H} = V_{1L} + r \cdot V_{1H} - V_{1L} + r \cdot V_{1L} = r\,(V_{1H} + V_{1L}) = r \cdot V_1.$$

Further, as $r > 1$, r^* is always positive.

For the case of $r <= 1$ (decreasing precipitation), an across-the-board decrease in precipitation was applied as follows:

$$V_2 = r \cdot V_{1L} + r \cdot V_{1H}$$

The adjustment factors can then be assembled as follows:

For the events above the 70th percentile, if

$r > 1$, then use r^*.

$r <= 1$, then use r.

For the events below the 70th percentile, if

$r > 1$, then use 1 (no change)

$r <= 1$, then use r.

PET Implementation

PET is simulated with the Penman-Monteith energy balance method. In addition to temperature and precipitation, the Penman-Monteith method requires as input dew point (or relative humidity), solar radiation, and wind. Because only a few stations have time series for all four additional variables that are complete over the entire 1970-2000 period, these variables are derived from the SWAT statistical weather generator (Neitsch et al. 2005). The SWAT weather generator database (wgn) contains the statistical data needed to generate representative daily climate data for the different stations. Adjustments to the wgn file parameters were made using monthly change factors for the NARCCAP dynamically downscaled scenarios. Specifically solar radiation, dew point temperature and wind speed were adjusted for each scenario (Table 4).

Table 4. SWAT Weather Generator Parameters and Adjustments Applied for Scenarios

SWAT wgn file Parameter	Description	Adjustment Applied
SOLARAV1	Average daily solar radiation for month (MJ/m2/day)	Adjusted based on surface downwelling shortwave radiation change (%)
DEWPT1	Average daily dew point temperature in month (ºC)	Additive delta value provided for climate scenario for each month
WNDAV1	Average daily wind speed in month (m/s)	Adjusted based on 10-meter wind speed change (%)

The probability of a wet day following a dry day in the month (PR_W1) and probability of a wet day following a wet day in the month (PR_W2) were kept the same as in the original wgn file. Based on discussion with EPA it was noted that systematic biases in the climate models being introduced by scale mismatch (between a 50-km grid and a station observation) for parameters in the weather generator like wet day/dry day timing and too many trace precipitation events relative to reality prohibit use of the climate models to determine these parameters and hence were kept the same as the original wgn file. Also an analysis of the dynamically downscaled raw 3-hourly time-series for the CRCM downscaling of the CGCM3 GCM demonstrated that the probability that a rainy day is followed by a rainy day (transition probability) did not change significantly at any of the five separate locations that were evaluated.

For the statistically downscaled climate scenarios in the BOR repository information on these additional meteorological variables is not provided. Many of these outputs are also unavailable from the archived raw GCM output. For these scenarios it was assumed that the statistical parameters remained unchanged at current conditions. While the lack of change is not physically realistic (e.g., changes in rainfall will cause changes in cloud cover and thus solar radiation reaching the land surface), this reflects the way in which output from these models is typically used.

One of the NARCCAP scenario archives (Scenario 5: CGCM3 downscaled with RCM3) does not include solar radiation, which may be affected by changes in cloud cover. Current condition statistics for solar radiation contained in the weather generator were used for this scenario. This does not appear to introduce a significant bias as the resulting PET predictions fall within the range of those derived from the other NARCCAP scenarios.

Endpoints for Change Analysis

Climate and land use change both have the potential to introduce significant changes in the hydrologic cycle. The mobilization and transport of pollutants will also be affected, both as a direct result of hydrologic changes and through changes in land cover and plant growth.

Hydrologic Endpoints

At the larger scale, flow volumes and the seasonal timing of flow are of immediate and obvious concern. Flows are analyzed in a variety of ways over the 30-year analysis period, including the minimum, median, mean, and maximum change relative to existing conditions among the different scenarios. Because of the uncertainties inherent in modeling at this scale, predictions of relative change are most relevant. In addition to basic flow statistics, comparisons are made for 100-year flood peak (fit with Log Pearson type III distribution; USGS 1982), average annual 7-day low flow, Richards-Baker flashiness index (a measure of the frequency and rapidity of short term changes in streamflow; Baker et al. 2004), and days to the centroid of mass for the annual flow on a water-year basis (i.e., days from previous October 1 at which half of the flow for the water year is achieved, an important indicator of changes in the snow accumulation and melt cycle).

Water Quality Endpoints

The SWAT model (operating at a daily time step) is most reliable in predicting monthly pollutant loads, while concentrations at shorter time steps may not be accurately simulated. Because the sediment load in-stream is often dominated by channel adjustment processes, which are highly site-specific and occur at a fine spatial scale, it is anticipated that precision in the prediction of sediment and sediment-associated pollutant loads will be relatively low. Nutrient balances can also be strongly affected by biological processes in the channels, which can only be roughly approximated at the scale of modeling proposed. Therefore, monthly and annual loads of sediment, phosphorus, and nitrogen are likely the most useful and reliable measures of water quality produced by the analysis and interpretation to finer time scales (e.g., concentration time series) is not recommended. Accordingly, the focus of comparison among scenarios is on monthly and average annual loads for TSS, total nitrogen, and total phosphorus.

As with the flow simulation, it is most appropriate to examine relative (rather than absolute) changes in simulated pollutant loads when comparing scenarios to current conditions. Although calibrated and validated, the models clearly have significant uncertainty in predicting current condition pollutant loads, and those loads are themselves very imprecisely known due to limited monitoring data.

Climate Scenario Results

Results of applying the 6 climate scenarios in the Lake Champlain SWAT model (Tetra Tech 2013) are summarized below in several ways. The different climate scenarios are in agreement on an increase in annual flow volumes, peak flows, and pollutant loads – but do not all agree on the sign of change for some of the other measures. Results are presented for all the major rivers and streams draining into Lake Champlain that are monitored by the Lake Champlain Basin Program.

- Poultney River
- Otter Creek
- Winooski River

- Lamoille River
- Missisquoi River
- Mettawee River – Barge Canal
- Ausable and Little Ausable Rivers
- La Platte River, Lewis Creek and Otter Creek
- Saranac and Salmon Rivers
- Boquet River
- Rock River and Pike River
- Great Chazy River and Little Chazy River

Poultney River

Table 5. Poultney River - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Flow	2.14%	13.86%	14.12%	24.87%
TSS	-3.29%	17.04%	16.70%	33.25%
TP	16.71%	33.31%	35.91%	56.40%

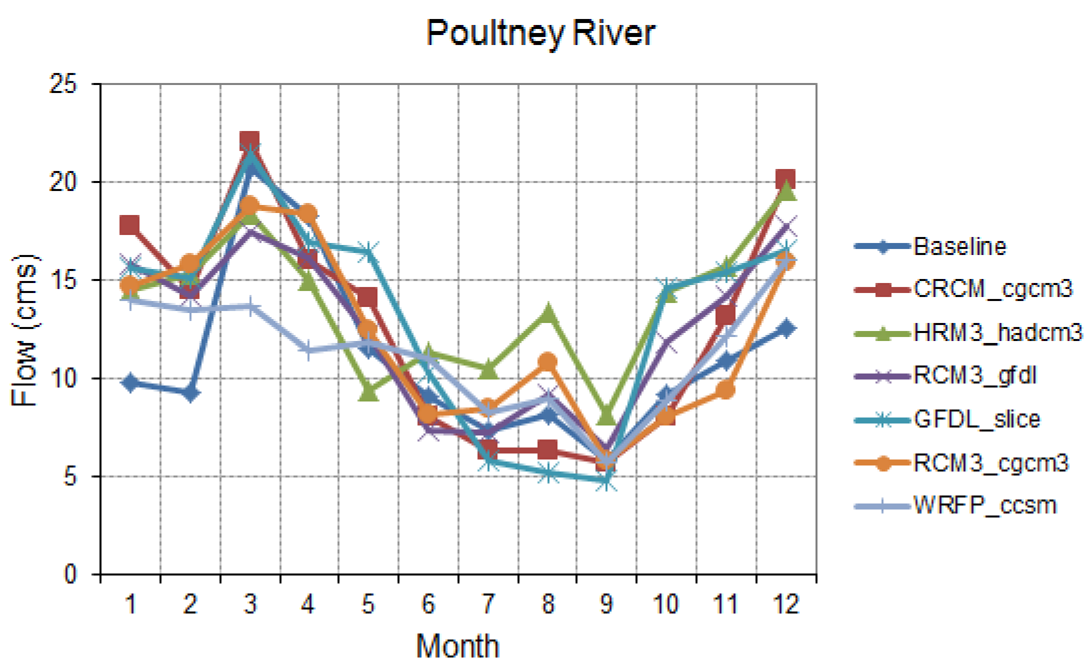


Figure 1. Average monthly flow volume across all NAARCAP scenarios – Poultney River

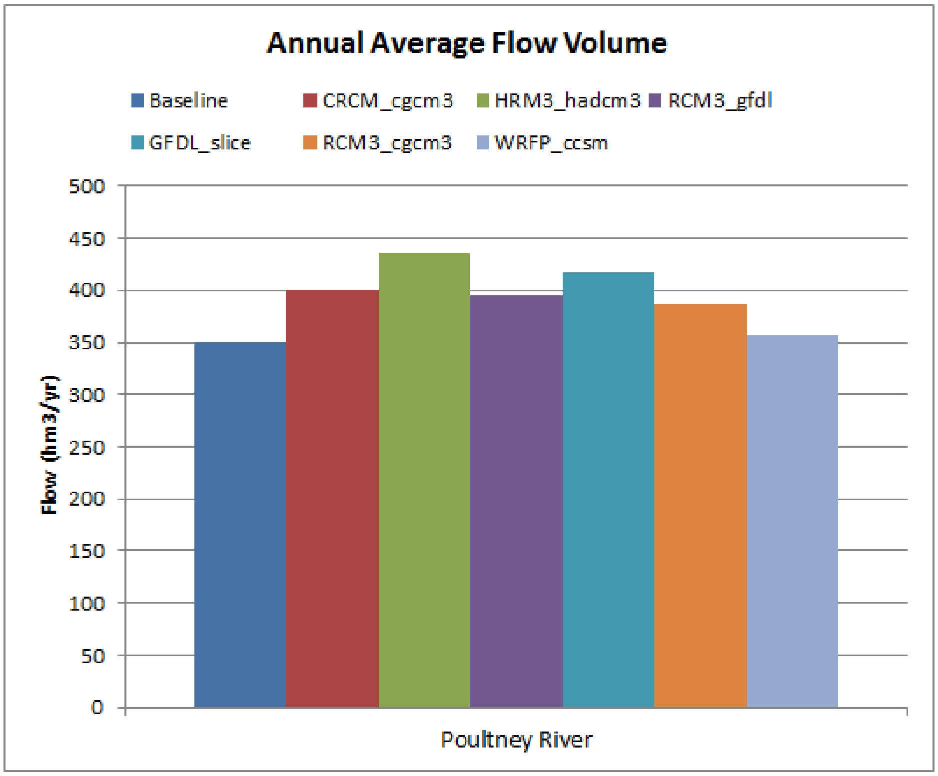


Figure 2. Average annual flow volume across all NAARCAP scenarios – Poultney River

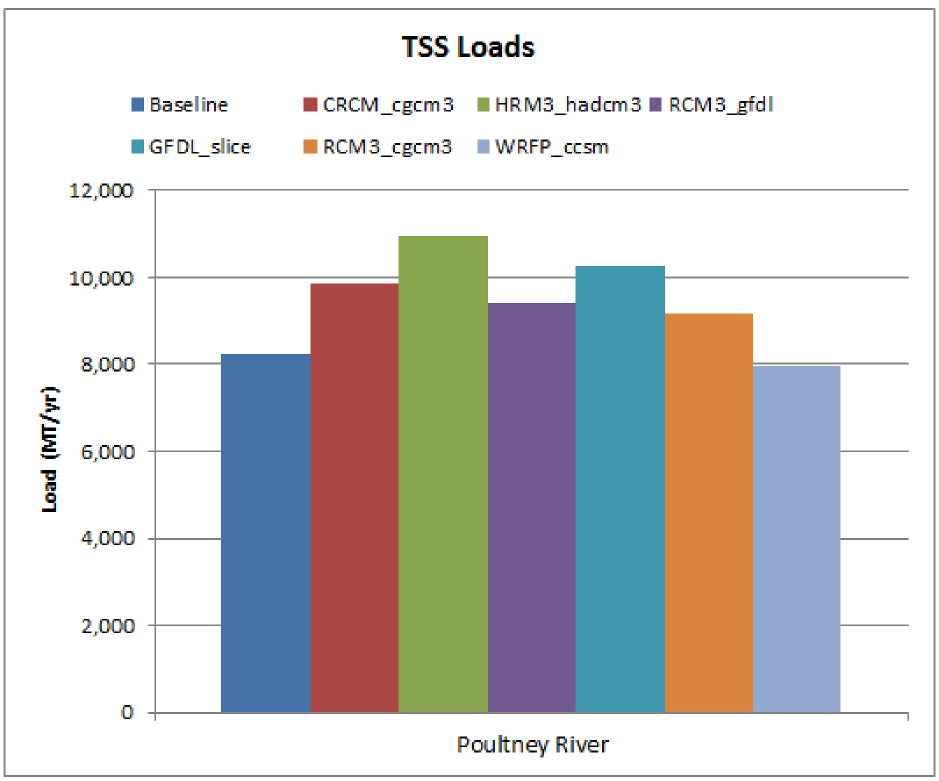


Figure 3. Average annual TSS load across all NAARCAP scenarios – Poultney River

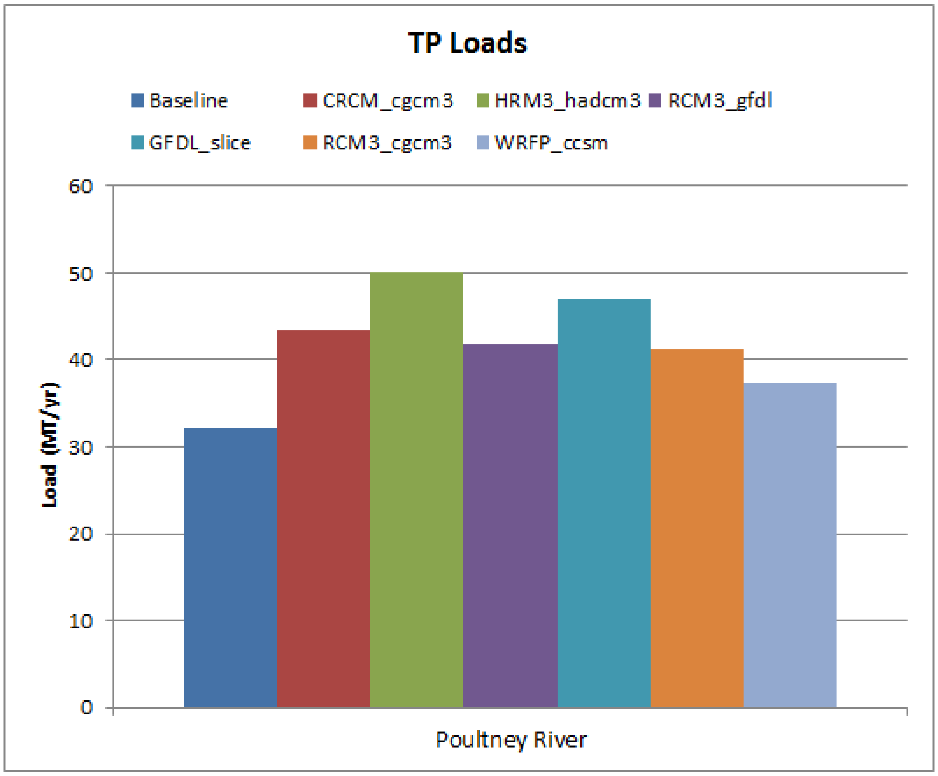


Figure 4. Average annual TP load across all NAARCAP scenarios – Poultney River

Otter Creek

Table 6. Otter Creek - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Flow	1.83%	11.33%	11.70%	21.30%
TSS	-2.67%	15.30%	14.70%	27.74%
TP	13.31%	28.14%	29.00%	42.56%

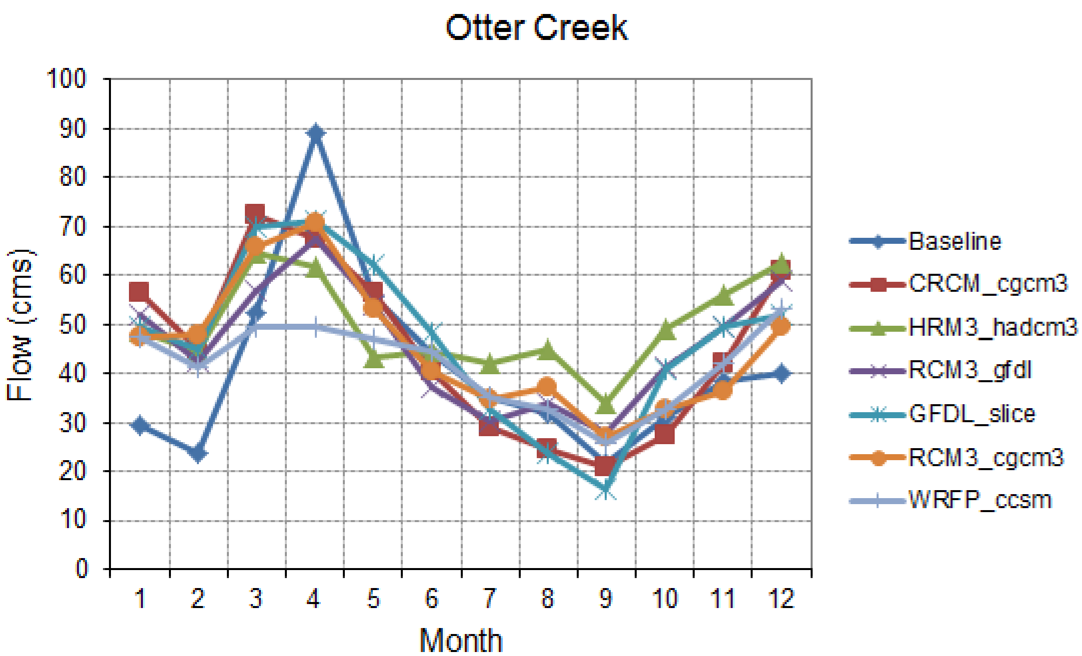


Figure 5. Average monthly flow volume across all NAARCAP scenarios – Otter Creek

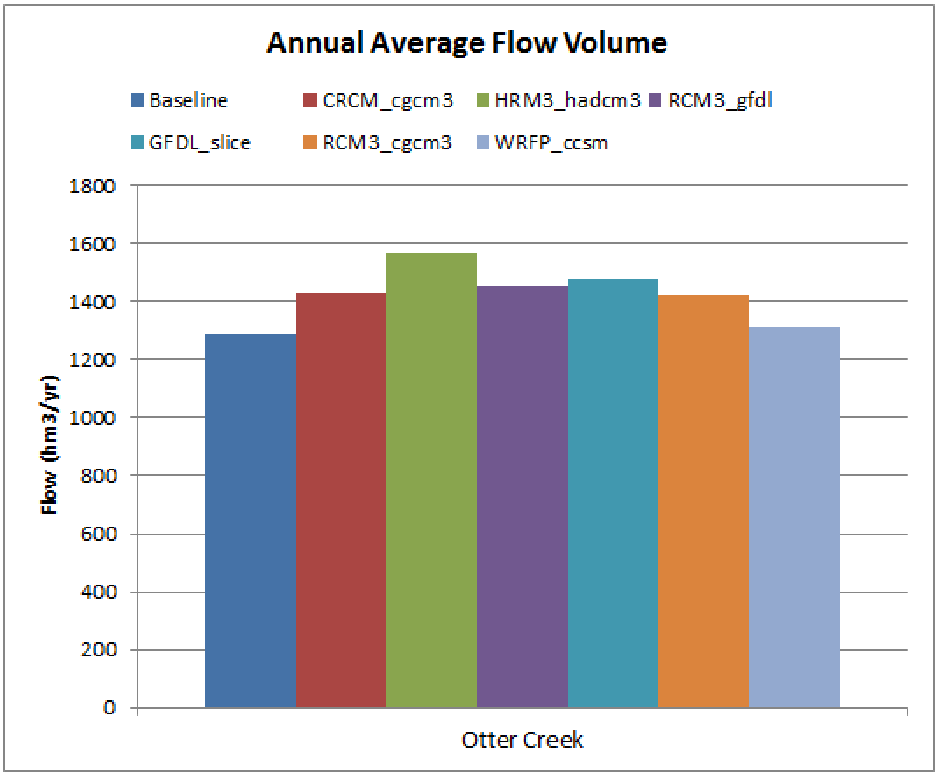


Figure 6. Average annual flow volume across all NAARCAP scenarios – Otter Creek

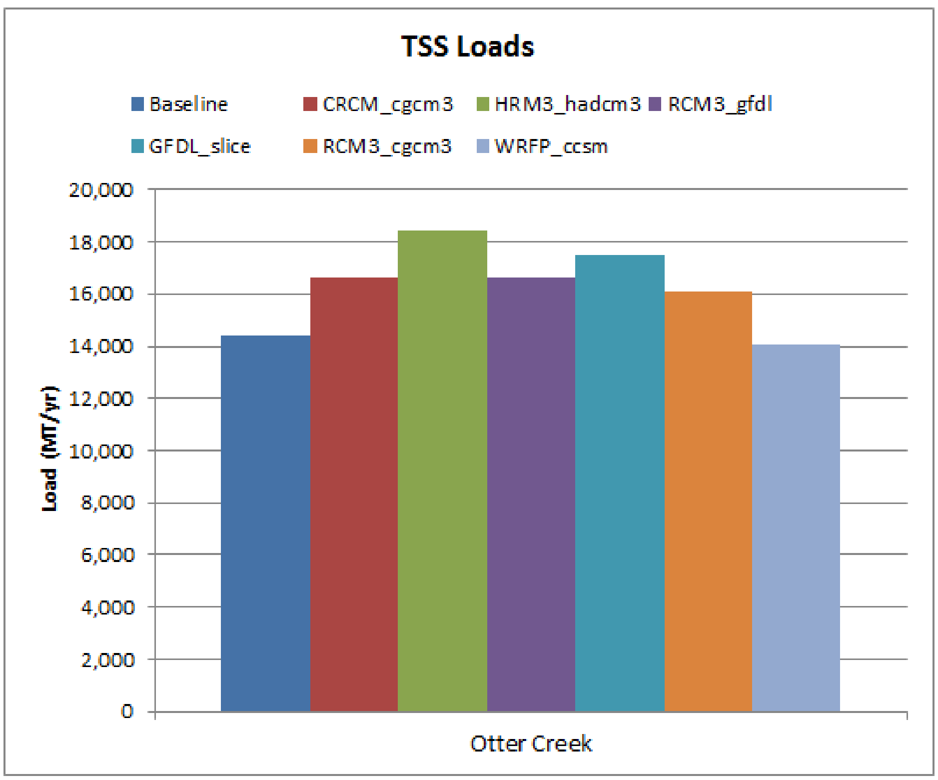


Figure 7. Average annual TSS load across all NAARCAP scenarios – Otter Creek

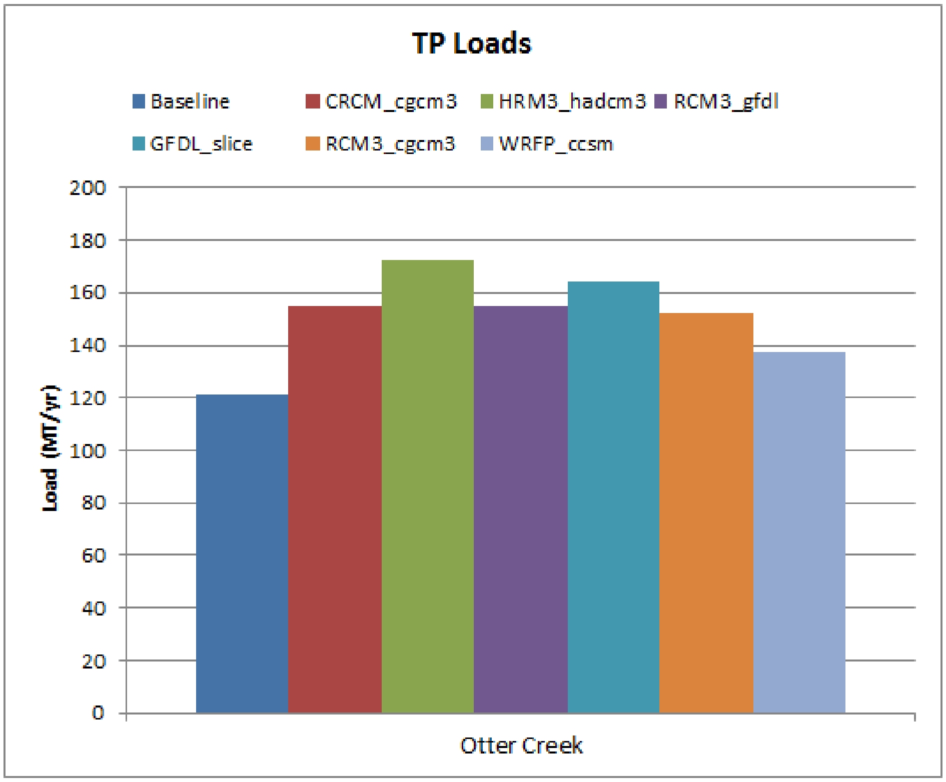


Figure 8. Average annual TP load across all NAARCAP scenarios – Otter Creek

Winooski River

Table 7. Winooski River - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Flow	1.31%	8.72%	8.77%	17.31%
TSS	-11.43%	6.90%	6.41%	19.03%
TP	8.81%	24.45%	26.11%	46.34%

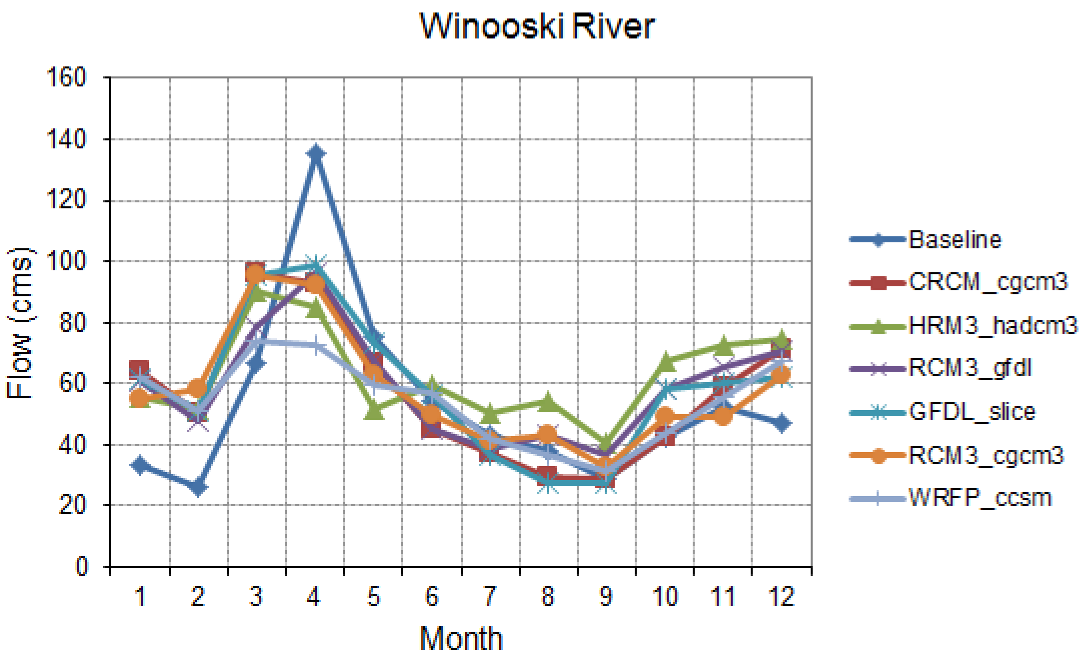


Figure 9. Average monthly flow volume across all NAARCAP scenarios – Winooski River

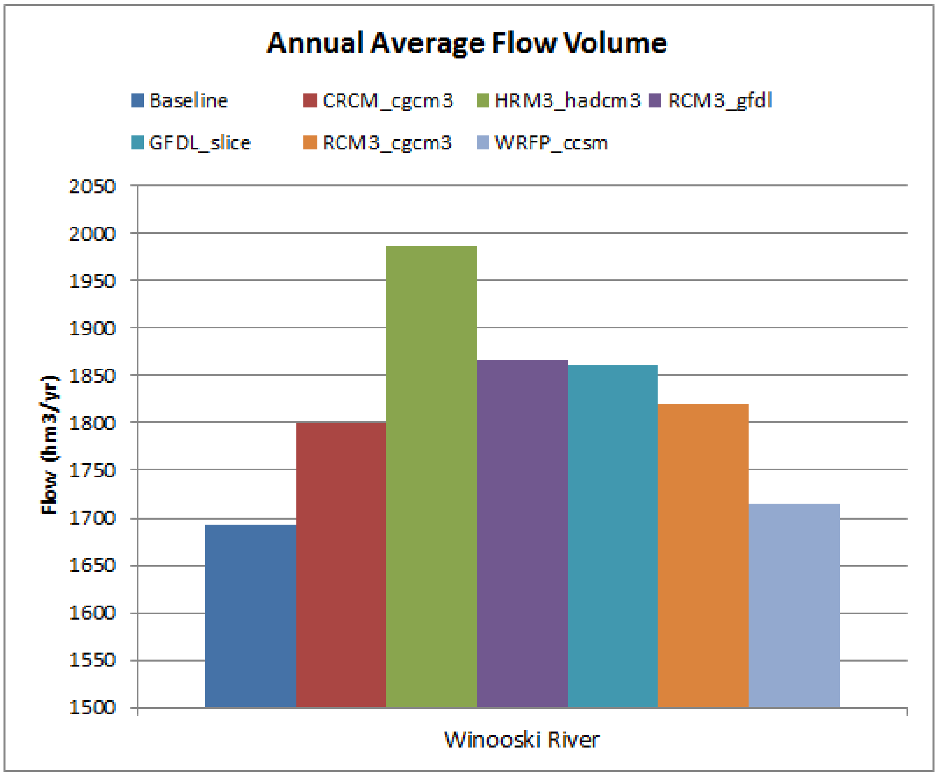


Figure 10. Average annual flow volume across all NAARCAP scenarios – Winooski River

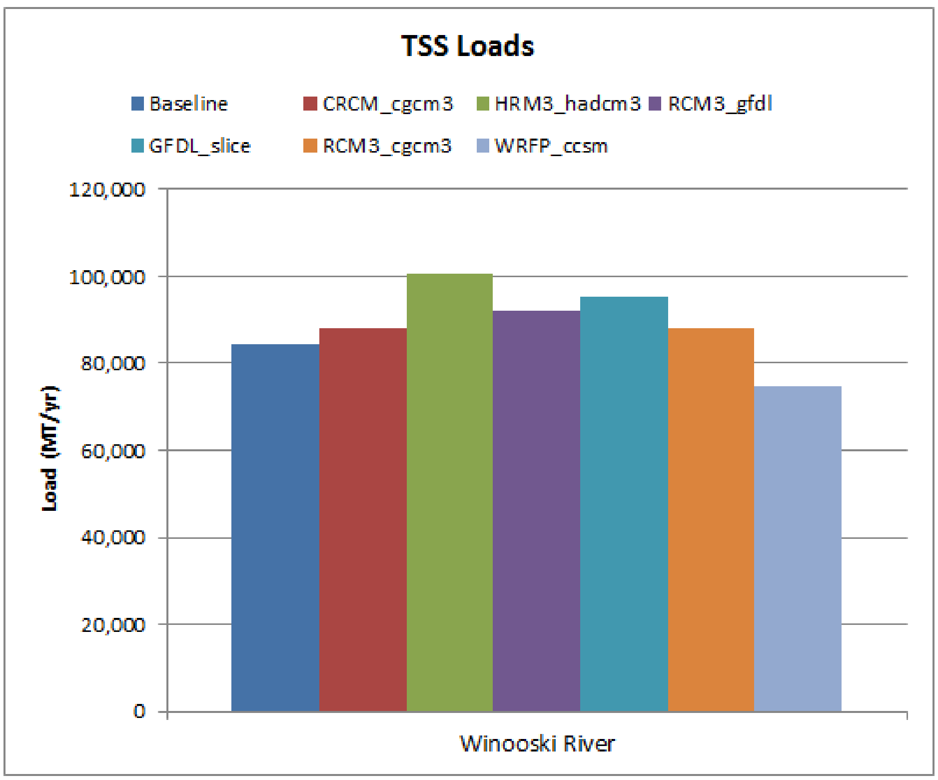


Figure 11. Average annual TSS load across all NAARCAP scenarios – Winooski River

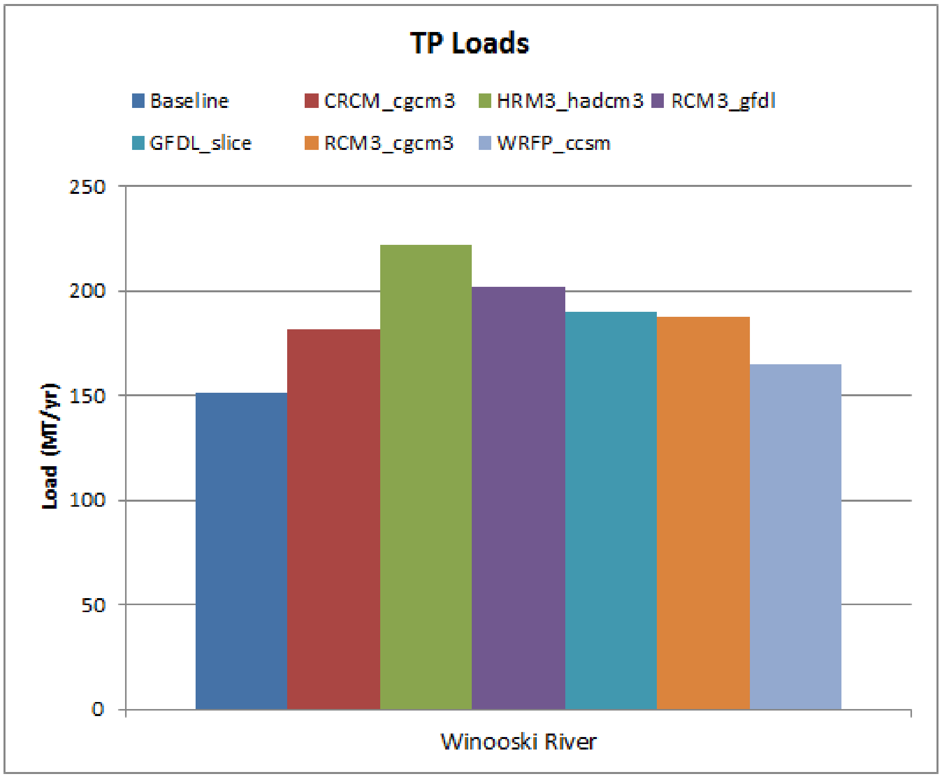


Figure 12. Average annual TP load across all NAARCAP scenarios – Winooski River

Lamoille River

Table 8. Lamoille River - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Flow	4.44%	14.85%	15.13%	26.45%
TSS	-3.96%	15.62%	15.57%	32.01%
TP	30.06%	43.06%	44.81%	63.02%

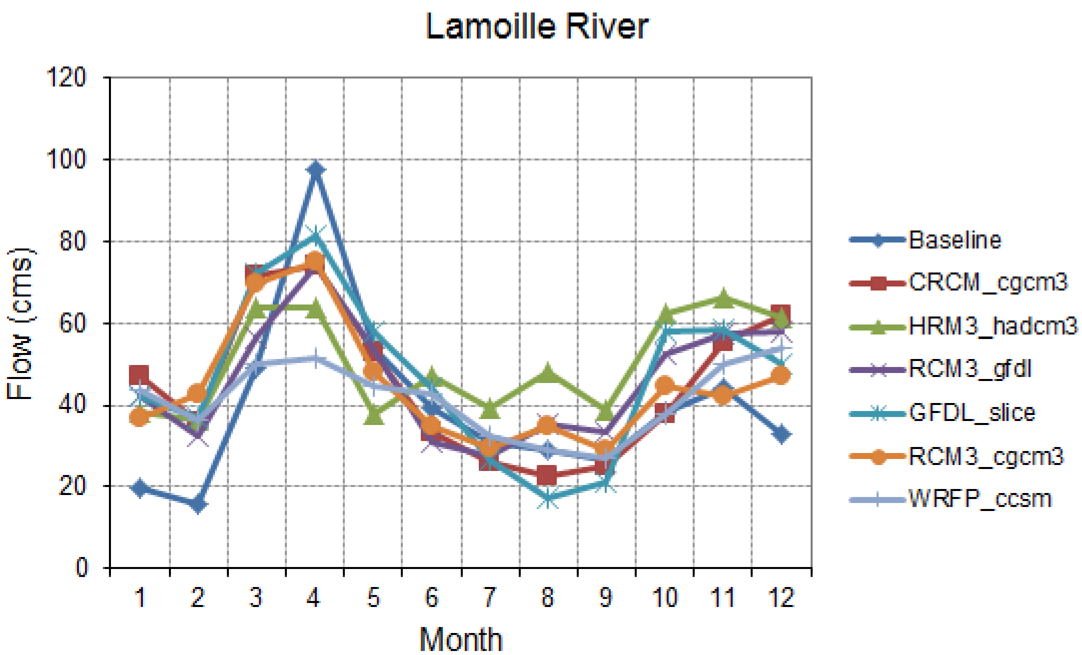


Figure 13. Average monthly flow volume across all NAARCAP scenarios – Lamoille River

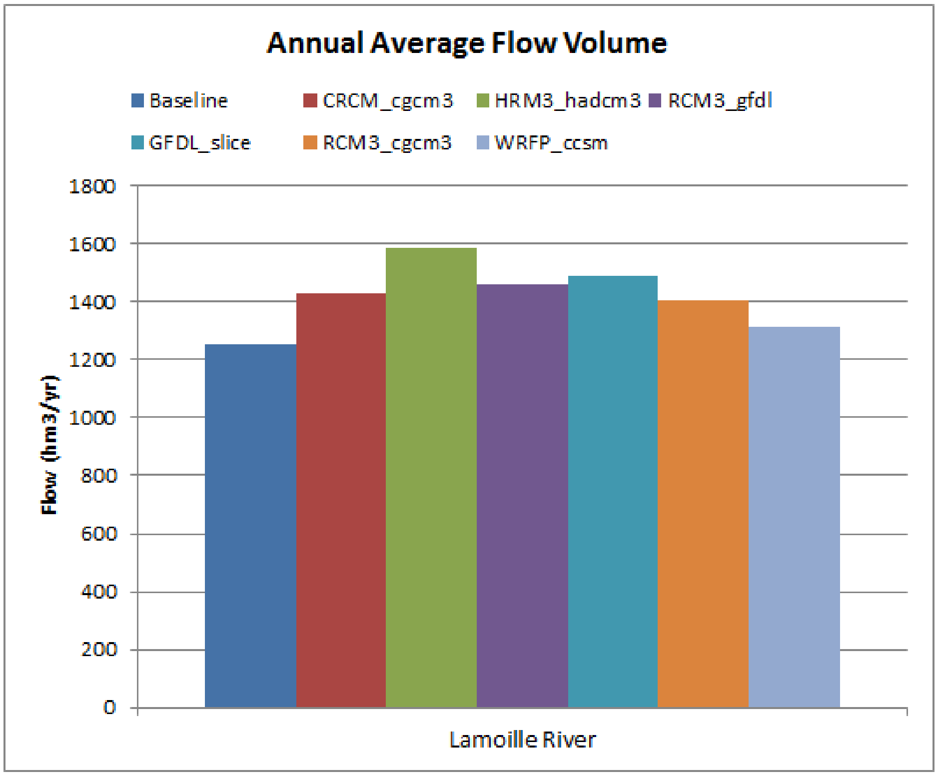


Figure 14. Average monthly flow volume across all NAARCAP scenarios – Lamoille River

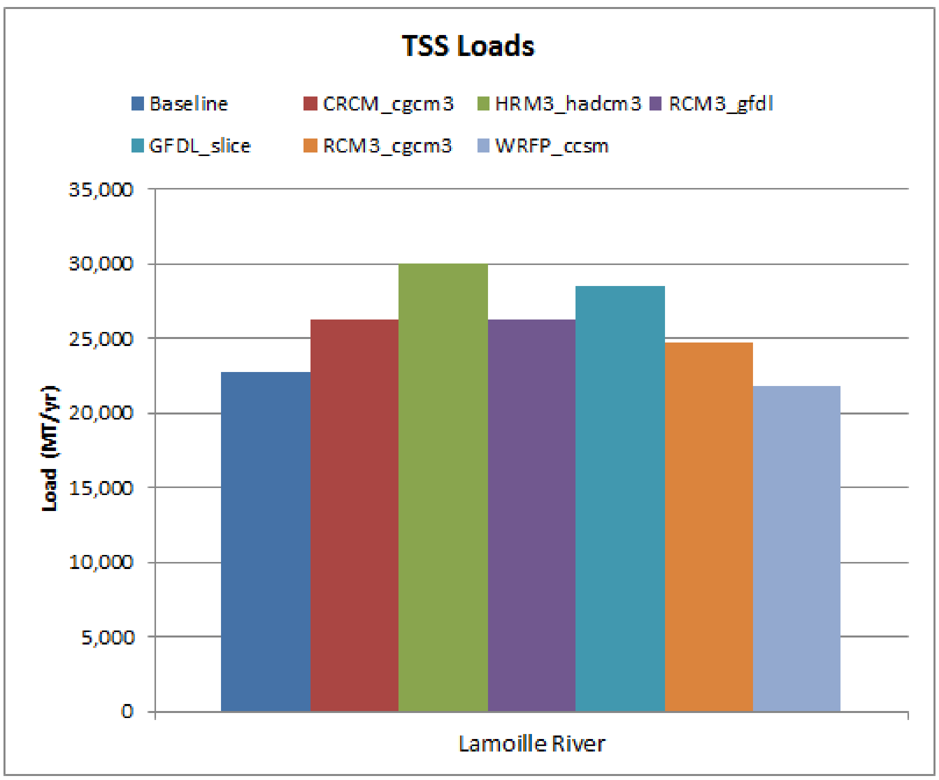


Figure 15. Average monthly TSS load across all NAARCAP scenarios – Lamoille River

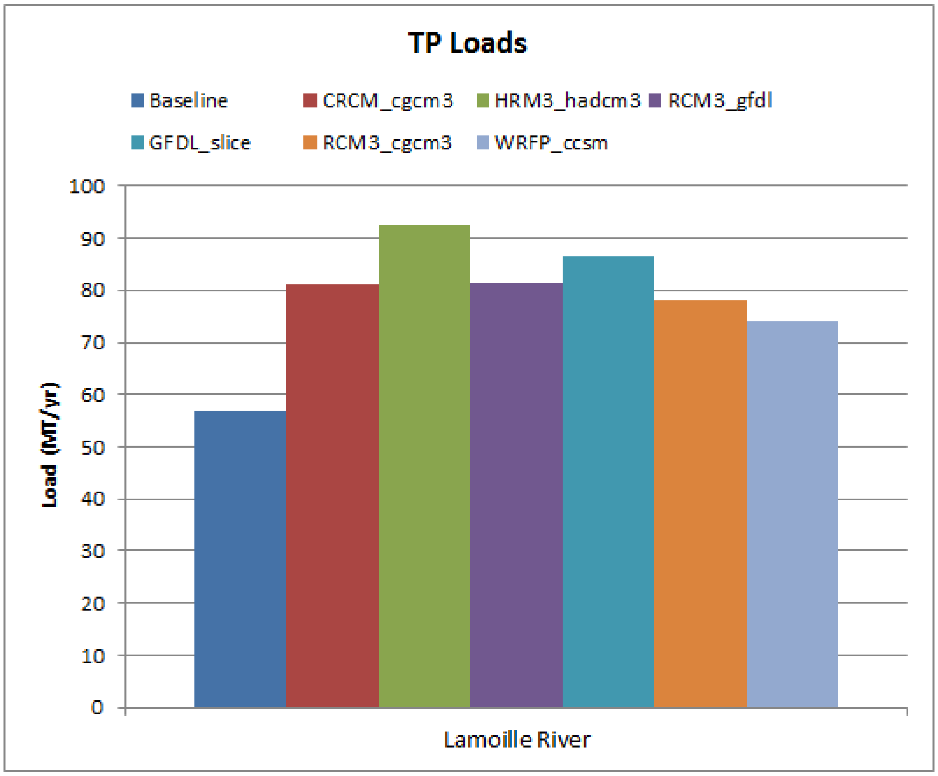


Figure 16. Average monthly TP load across all NAARCAP scenarios – Lamoille River

Missisquoi River

Table 9. Missisquoi River - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Flow	0.63%	11.43%	10.24%	15.40%
TSS	-22.83%	-2.53%	-3.18%	12.46%
TP	13.36%	31.46%	30.44%	42.10%

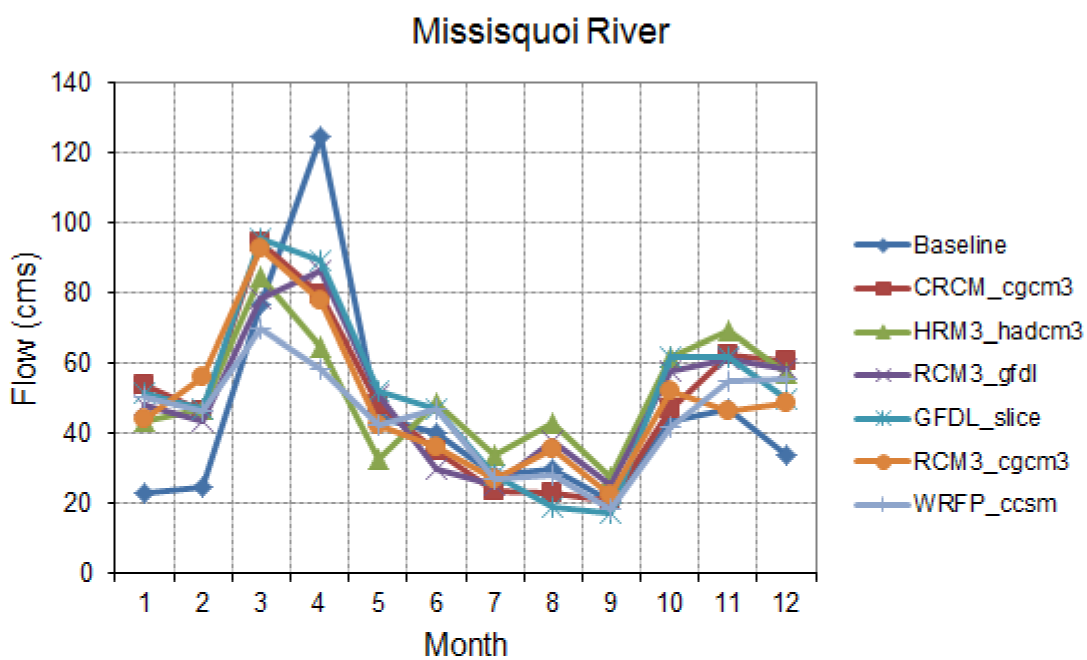


Figure 17. Average monthly flow volume across all NAARCAP scenarios – Missisquoi River

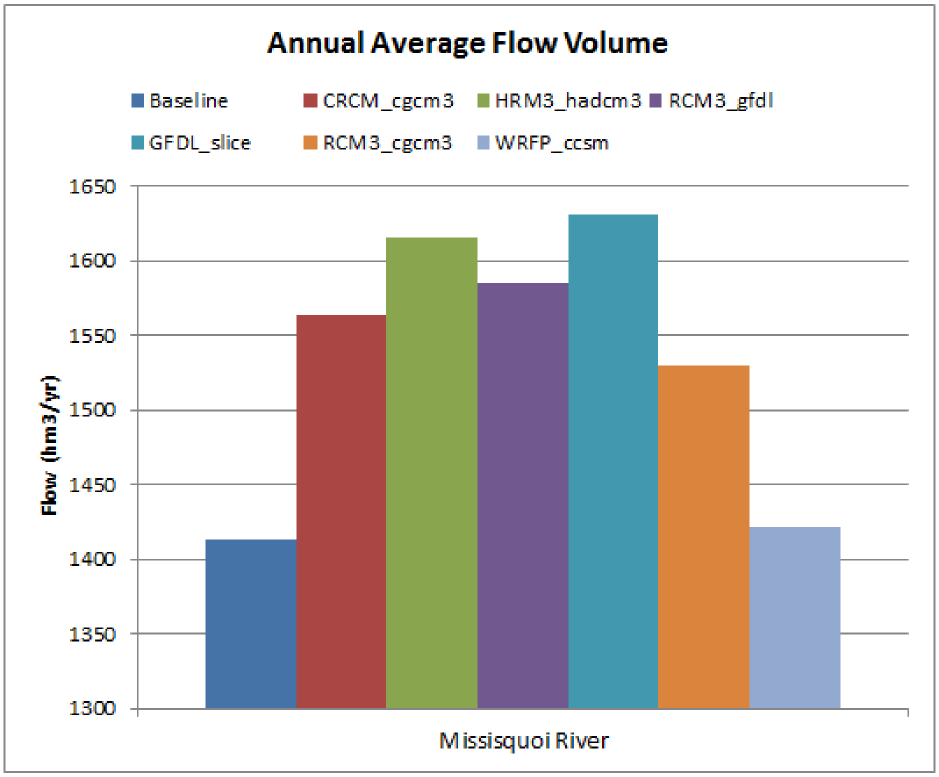


Figure 18. Average monthly flow volume across all NAARCAP scenarios – Missisquoi River

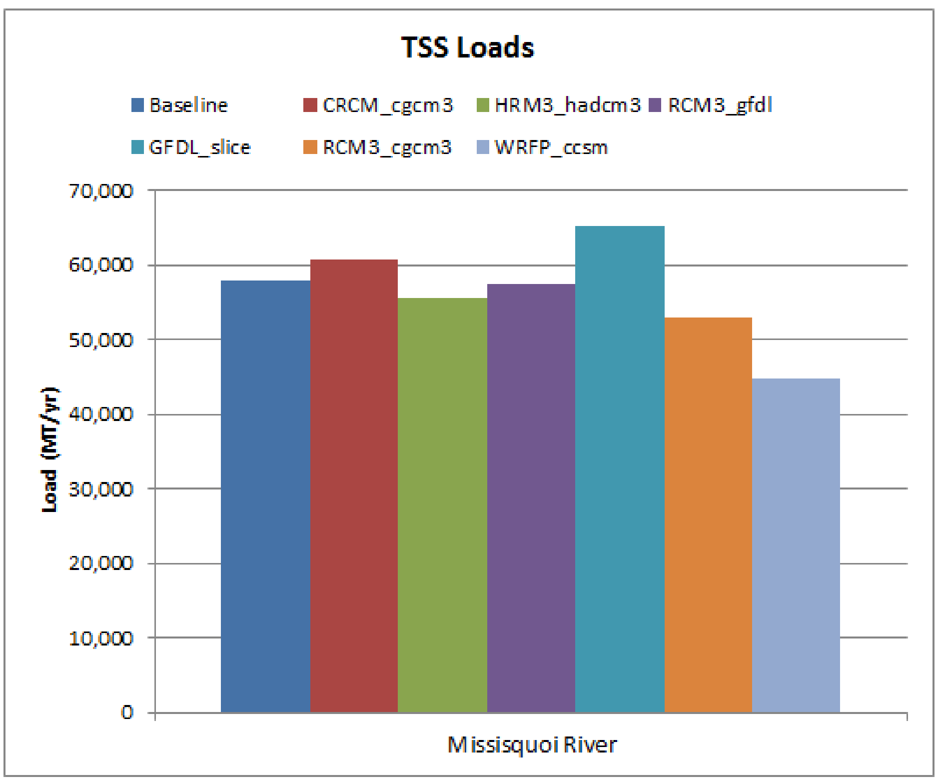


Figure 19. Average monthly TSS load across all NAARCAP scenarios – Missisquoi River

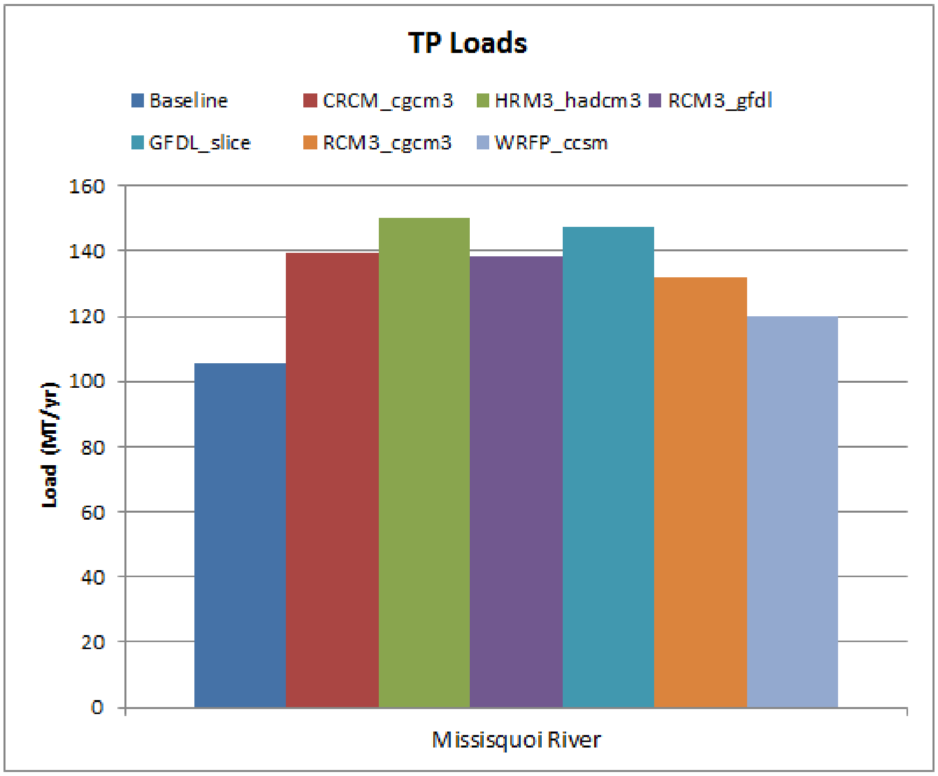


Figure 20. Average monthly TP load across all NAARCAP scenarios – Missisquoi River

Mettawee River

Table 10. Mettawee River - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Flow	3.12%	14.19%	13.57%	20.69%
TSS	-4.84%	18.74%	16.62%	27.61%
TP	24.24%	39.80%	40.69%	57.75%

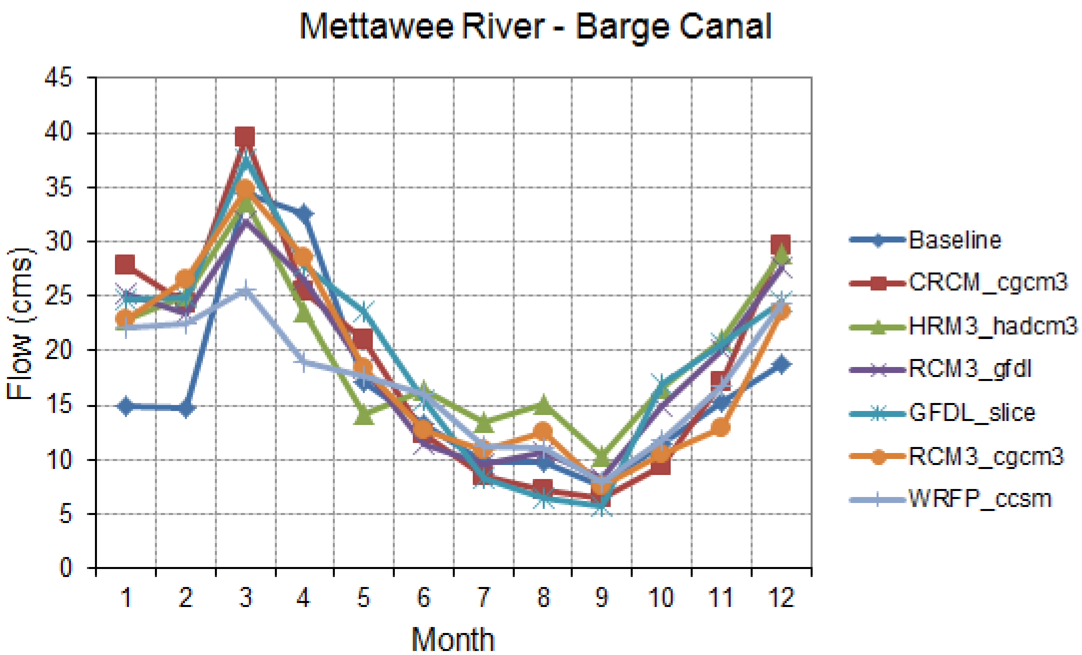


Figure 21. Average monthly flow volume across all NAARCAP scenarios – Mettawee River

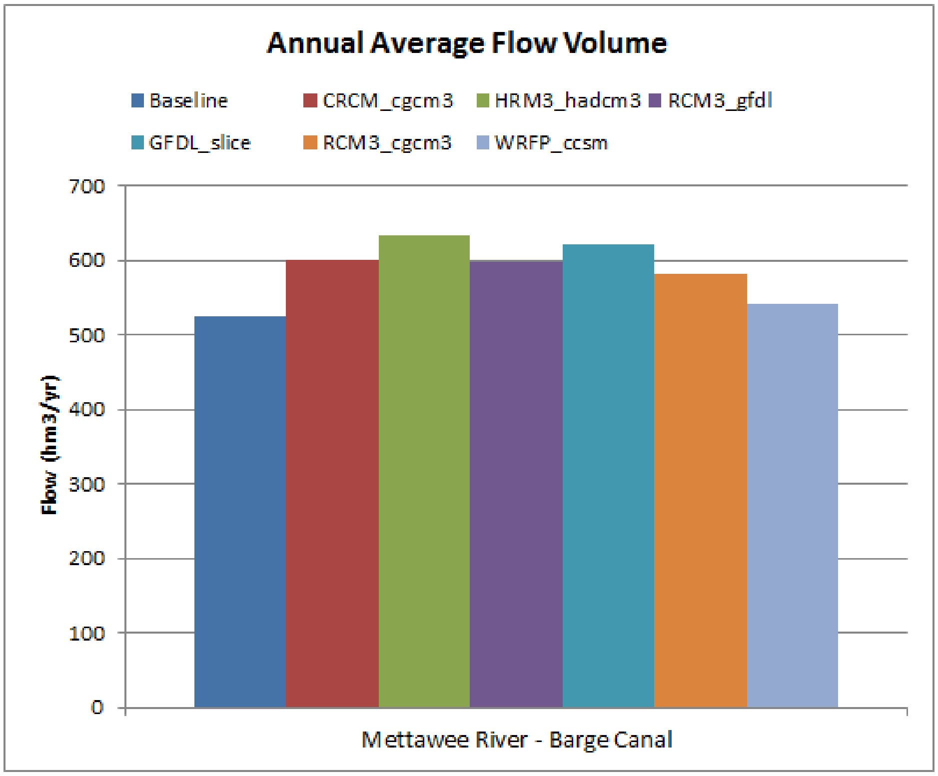


Figure 22. Average monthly flow volume across all NAARCAP scenarios – Mettawee River

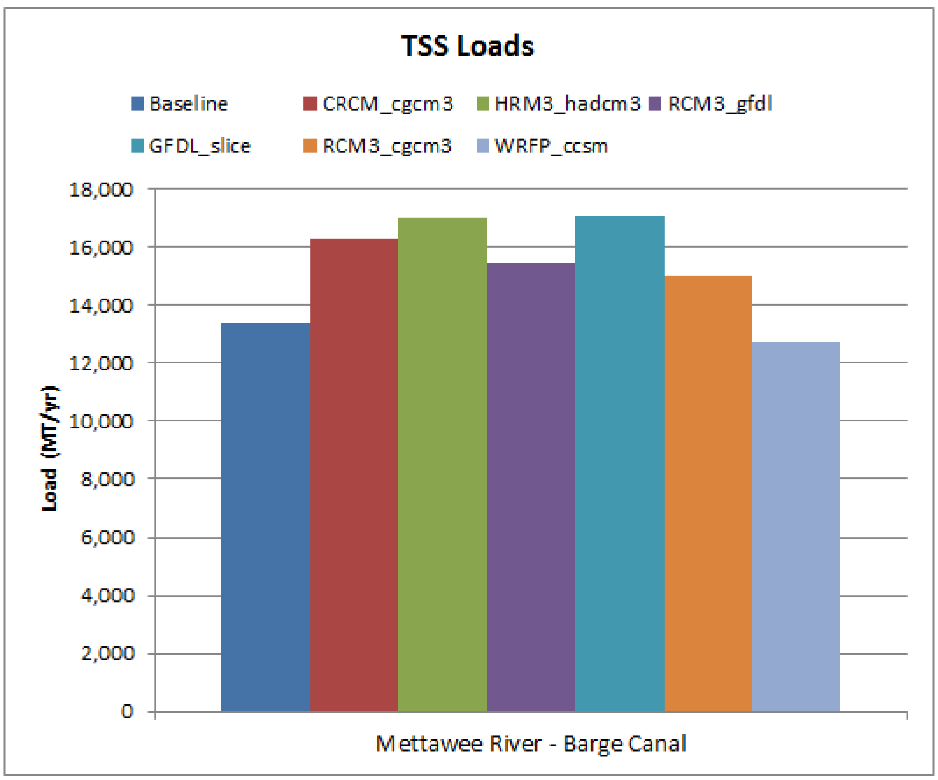


Figure 23. Average monthly TSS load across all NAARCAP scenarios – Mettawee River

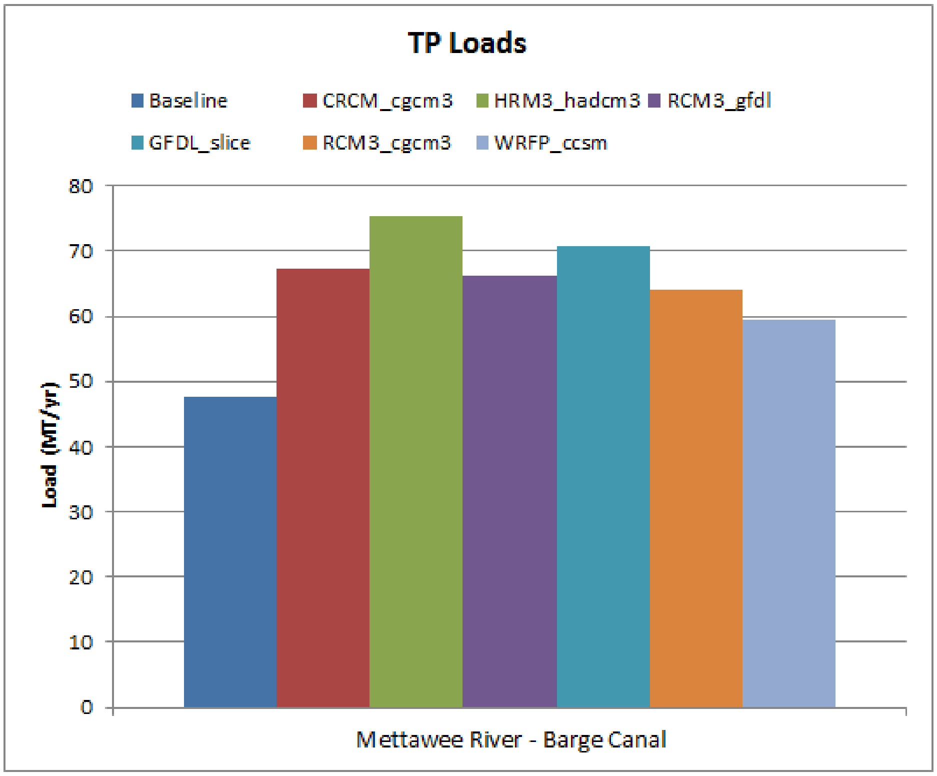
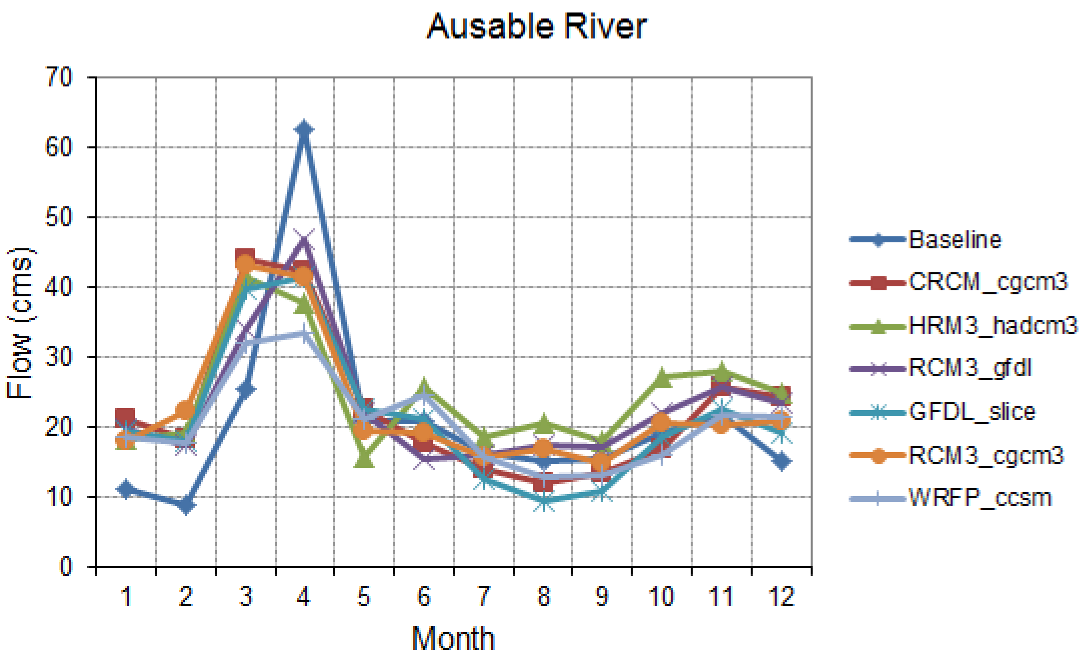


Figure 24. Average monthly TP load across all NAARCAP scenarios – Mettawee River

Ausable River and Little Ausable River

Table 11. Ausable - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Ausable River				
Flow	-1.74%	7.79%	6.87%	16.66%
TSS	-16.78%	3.86%	1.72%	19.37%
TP	-6.58%	5.23%	4.33%	18.34%
Little Ausable River				
Flow	9.32%	25.51%	26.62%	46.47%
TSS	13.25%	32.72%	40.46%	87.84%
TP	16.81%	37.63%	44.28%	89.01%



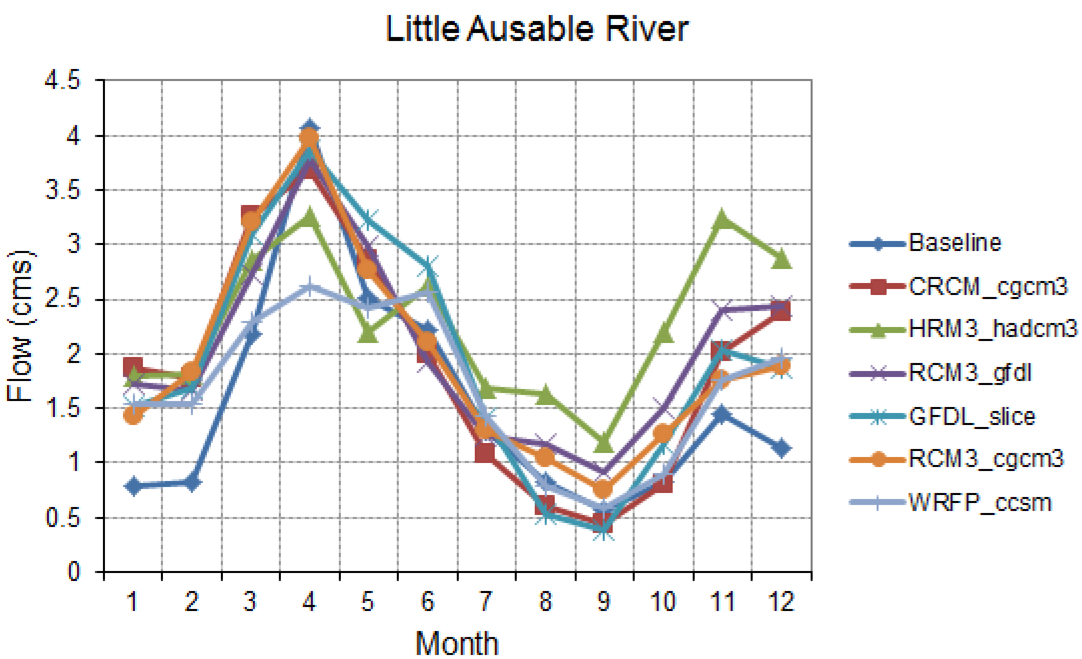


Figure 25. Average monthly flow volume across all NAARCAP scenarios - Ausable

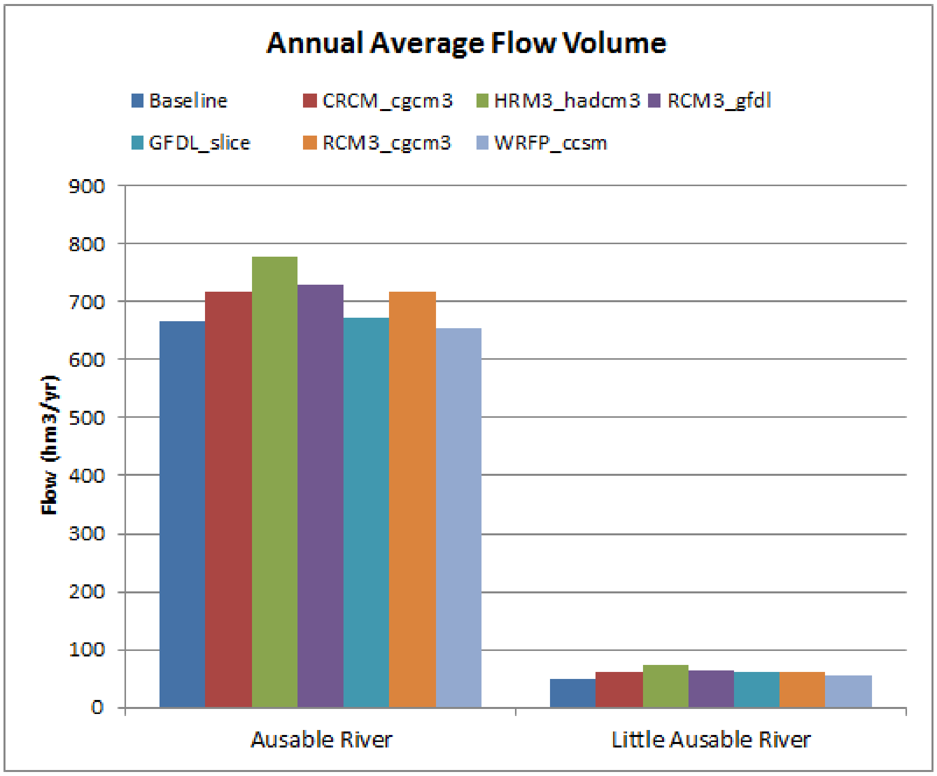


Figure 26. Average monthly flow volume across all NAARCAP scenarios - Ausable

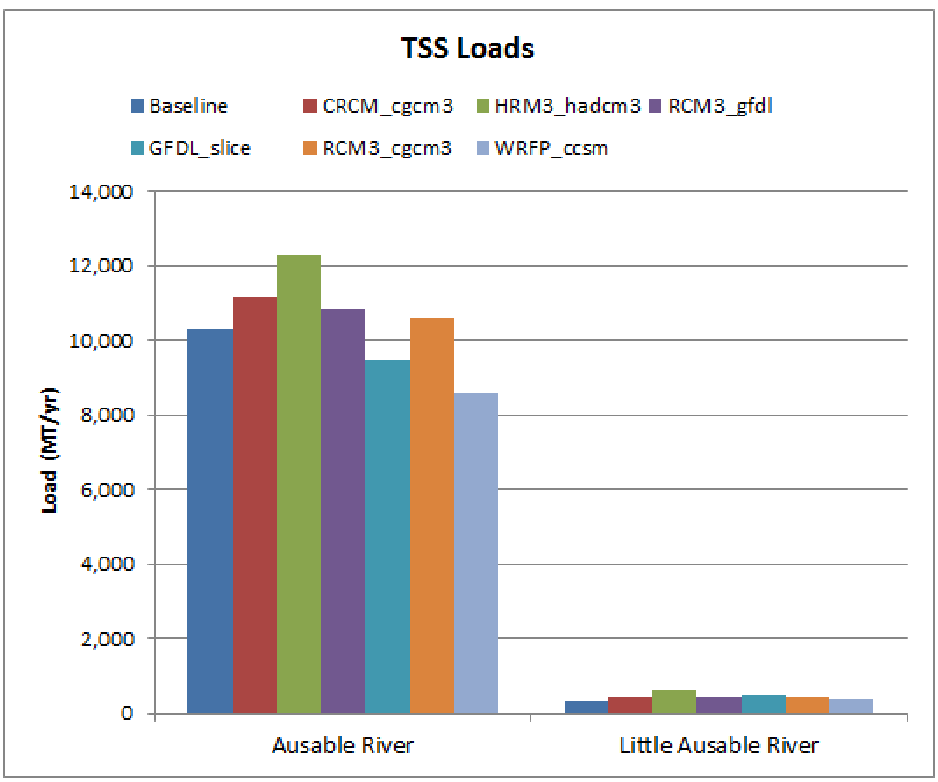


Figure 27. Average monthly TSS load across all NAARCAP scenarios - Ausable

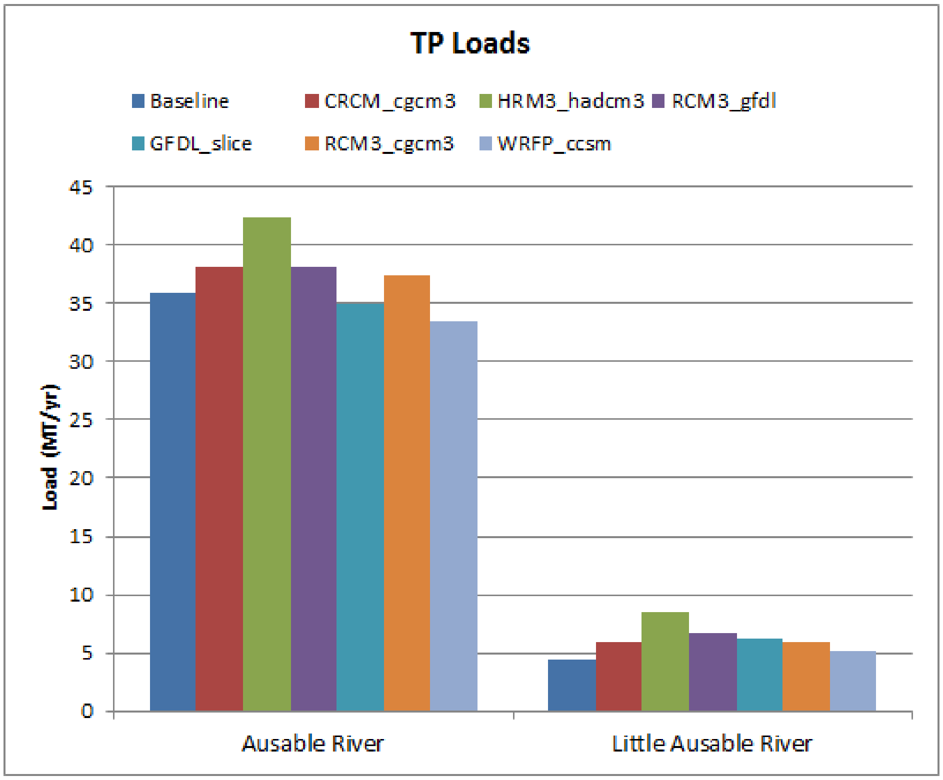


Figure 28. Average monthly TP load across all NAARCAP scenarios - Ausable

LaPlatte River, Lewis Creek and Little Otter Creek

Table 12. La Platte River, Lewis and Little Otter Creeks - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
LaPlatte River				
Flow	-12.46%	-2.38%	-2.91%	2.92%
TSS	-12.46%	1.94%	0.96%	12.99%
TP	32.67%	50.68%	49.91%	63.23%
Lewis Creek				
Flow	-14.99%	-6.32%	-6.52%	0.07%
TSS	-39.38%	-32.28%	-29.51%	-14.67%
TP	14.10%	30.54%	31.35%	44.09%
Little Otter Creek				
Flow	-13.14%	-4.42%	-4.74%	-0.02%
TSS	-27.69%	-13.30%	-13.73%	-3.87%
TP	26.16%	42.87%	43.11%	55.02%

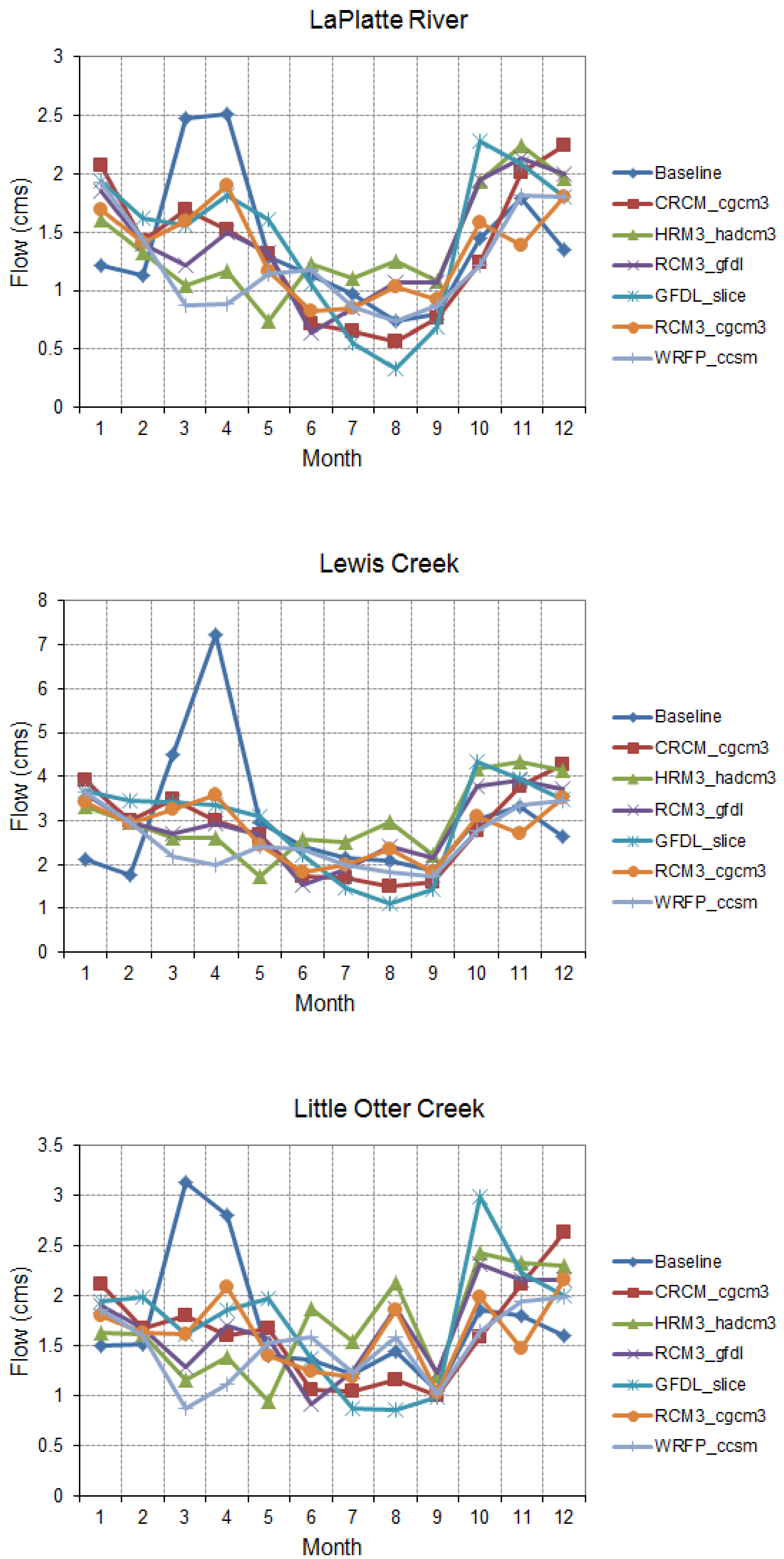


Figure 29. Average monthly flow volume across all NAARCAP scenarios – LaPlatte, Lewis, Little Otter

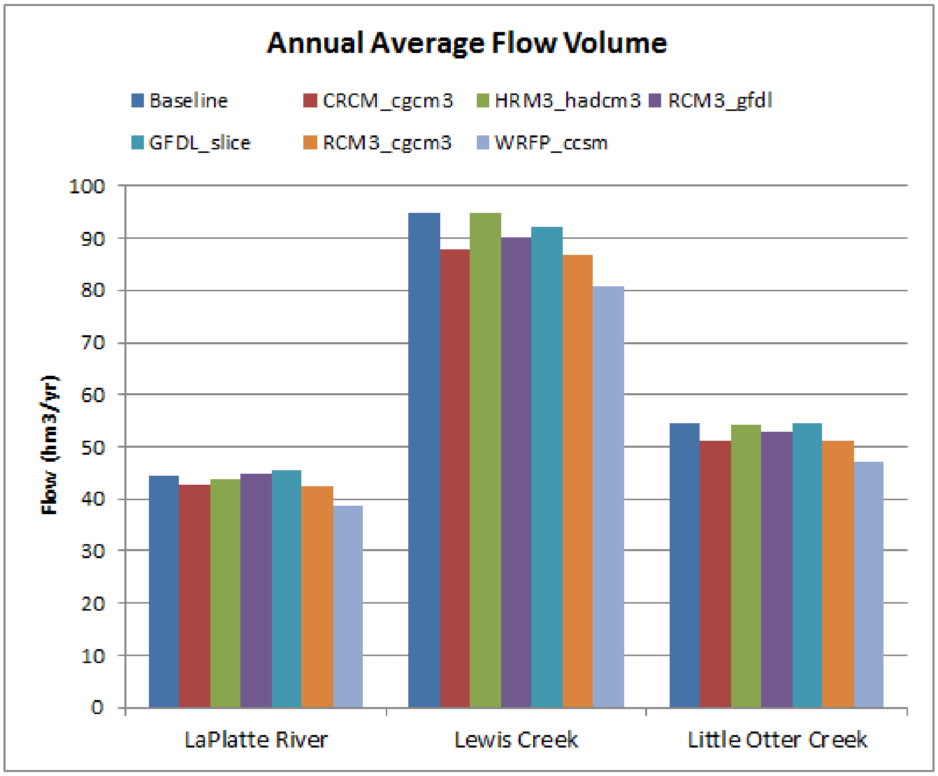


Figure 30. Average annual flow volume across all NAARCAP scenarios – LaPlatte, Lewis, Little Otter

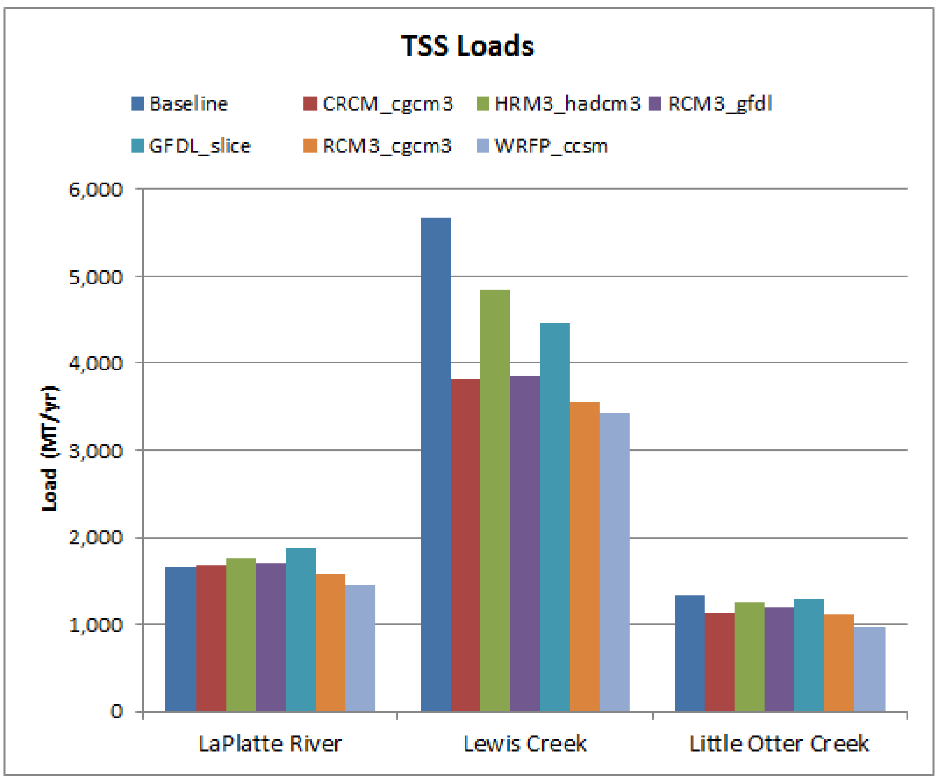


Figure 31. Average annual TSS load across all NAARCAP scenarios – LaPlatte, Lewis, Little Otter

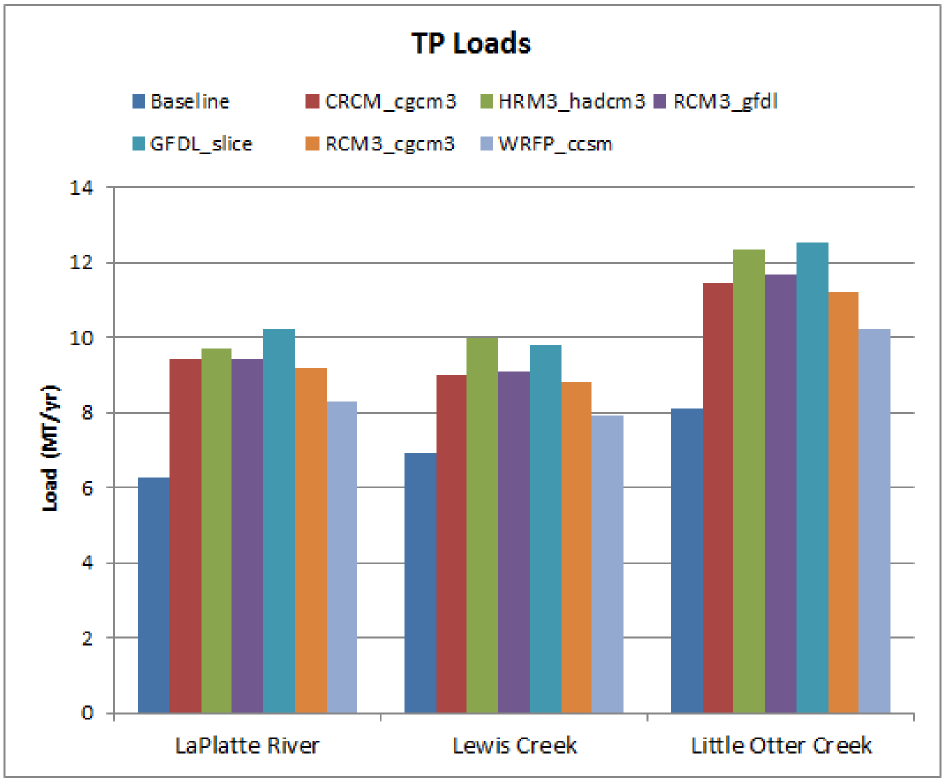
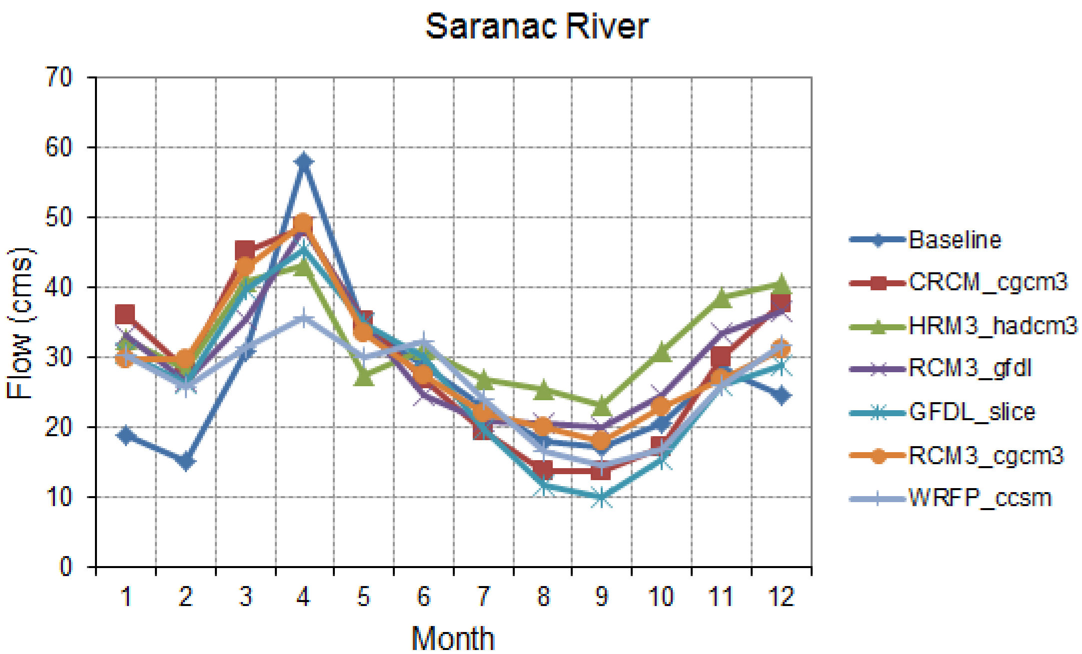


Figure 32. Average annual TP load across all NAARCAP scenarios – LaPlatte, Lewis, Little Otter

Saranac River and Salmon River

Table 13. Saranac and Salmon Rivers - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Saranac River				
Flow	-0.67%	11.11%	9.66%	22.64%
TSS	-2.91%	14.70%	13.02%	32.69%
TP	-8.55%	2.26%	1.54%	11.89%
Salmon River				
Flow	4.51%	18.05%	17.29%	27.22%
TSS	0.33%	22.10%	21.64%	43.51%
TP	18.93%	33.33%	33.05%	46.69%



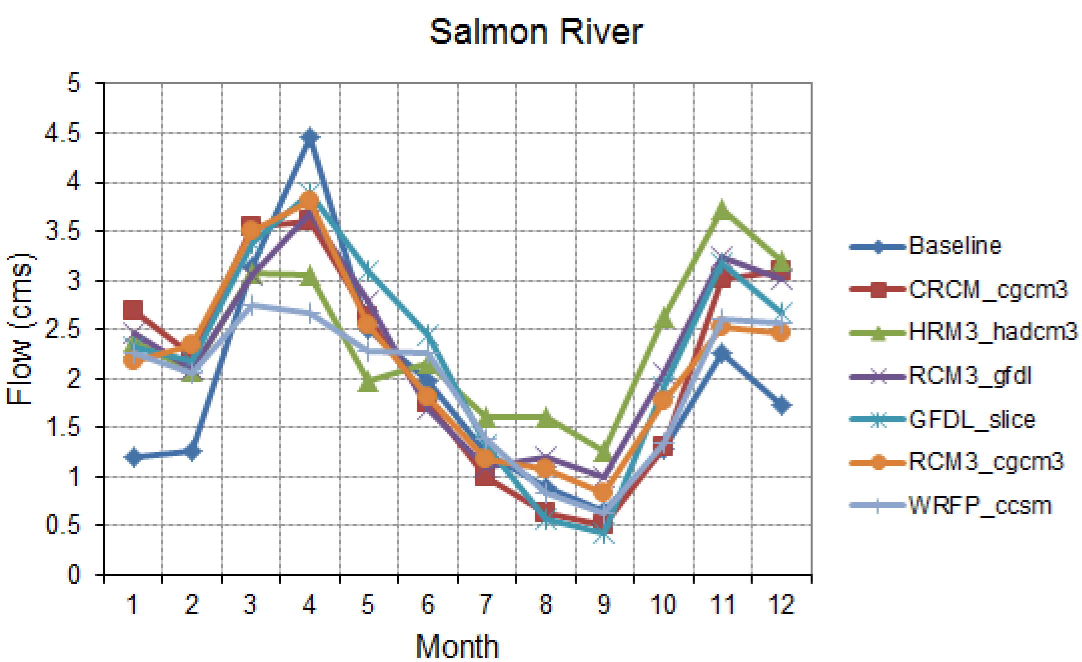


Figure 33. Average monthly flow volume across all NAARCAP scenarios – Saranac and Salmon Rivers

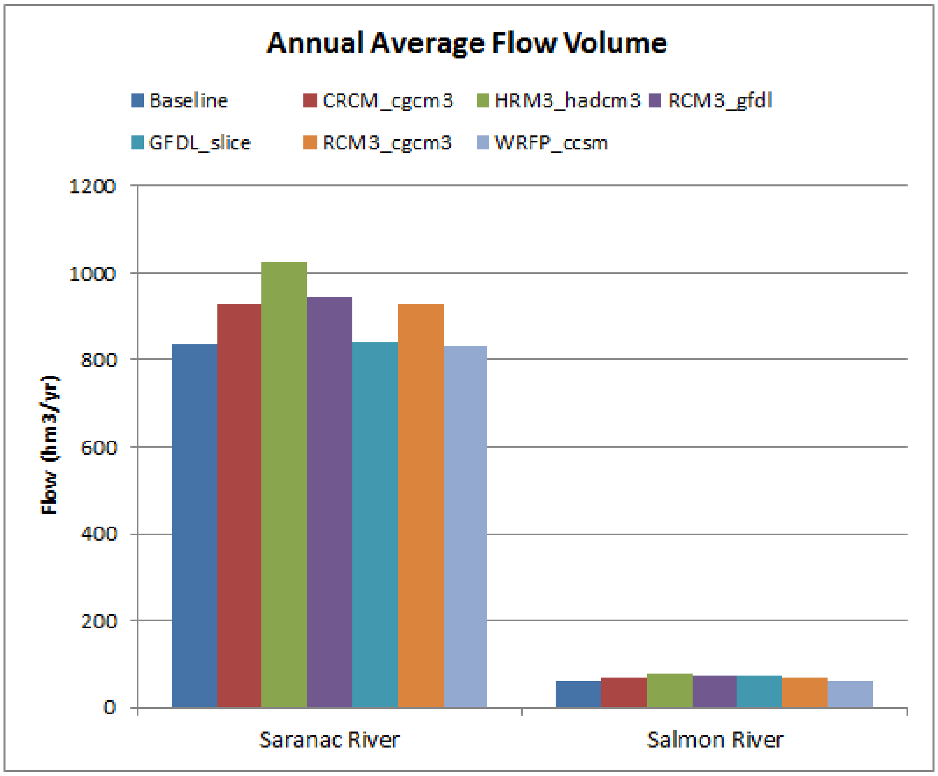


Figure 34. Average monthly flow volume across all NAARCAP scenarios – Saranac and Salmon Rivers

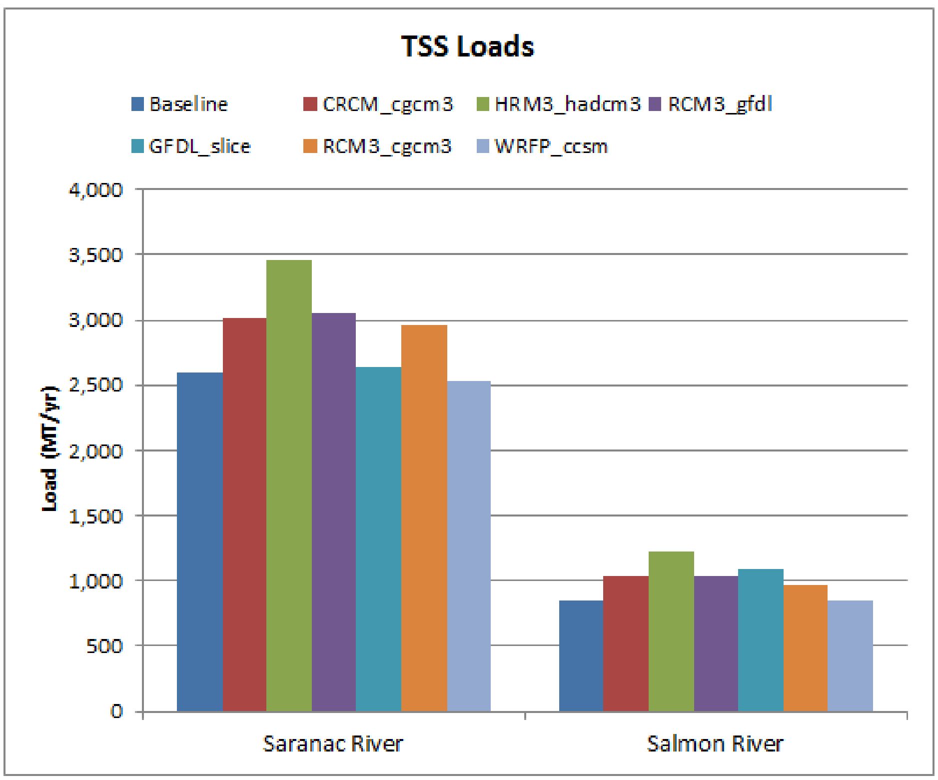


Figure 35. Average monthly TSS load across all NAARCAP scenarios – Saranac and Salmon Rivers

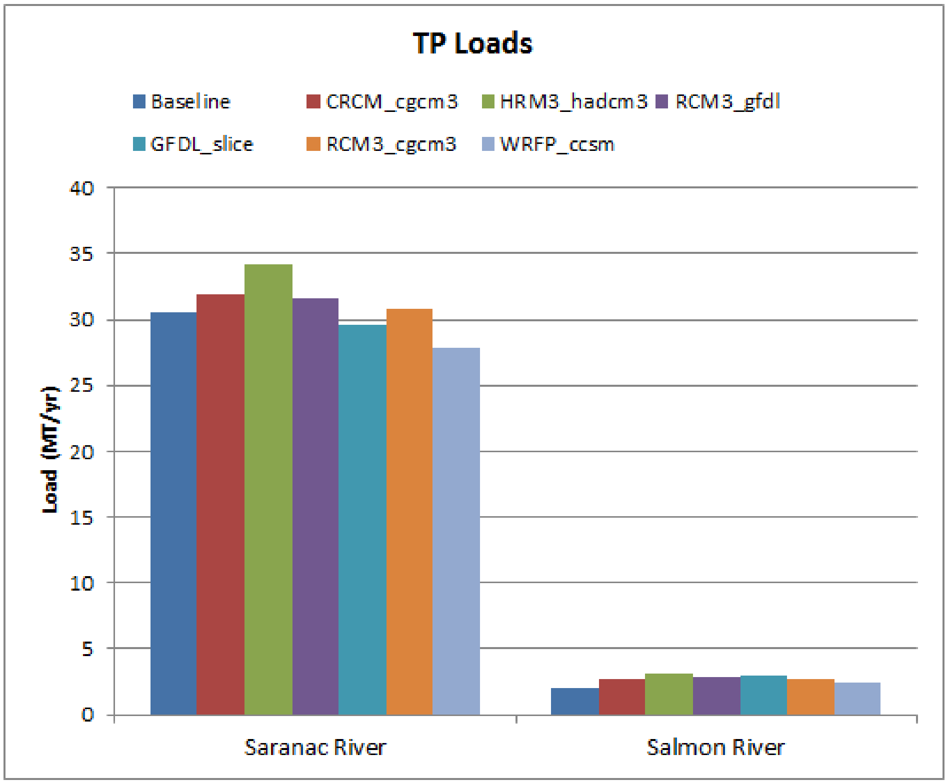


Figure 36. Average monthly TP load across all NAARCAP scenarios – Saranac and Salmon Rivers

Boquet River

Table 14. Boquet River - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Flow	1.29%	11.39%	10.23%	13.68%
TSS	-9.88%	14.90%	12.92%	24.18%
TP	14.20%	30.34%	28.21%	34.26%

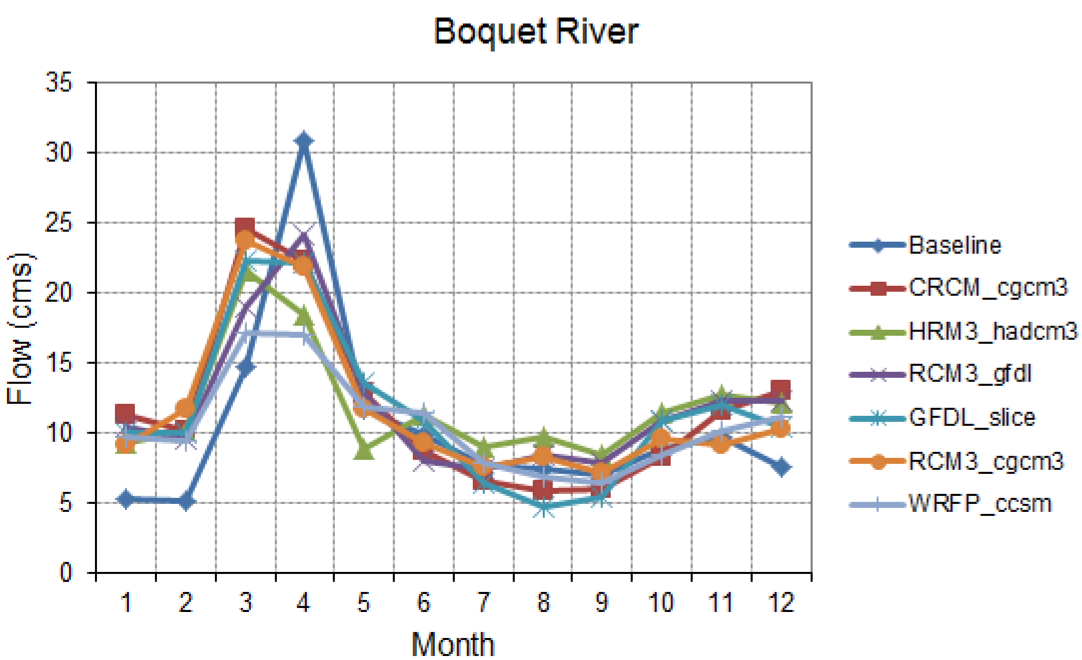


Figure 37. Average monthly flow volume across all NAARCAP scenarios – Boquet River

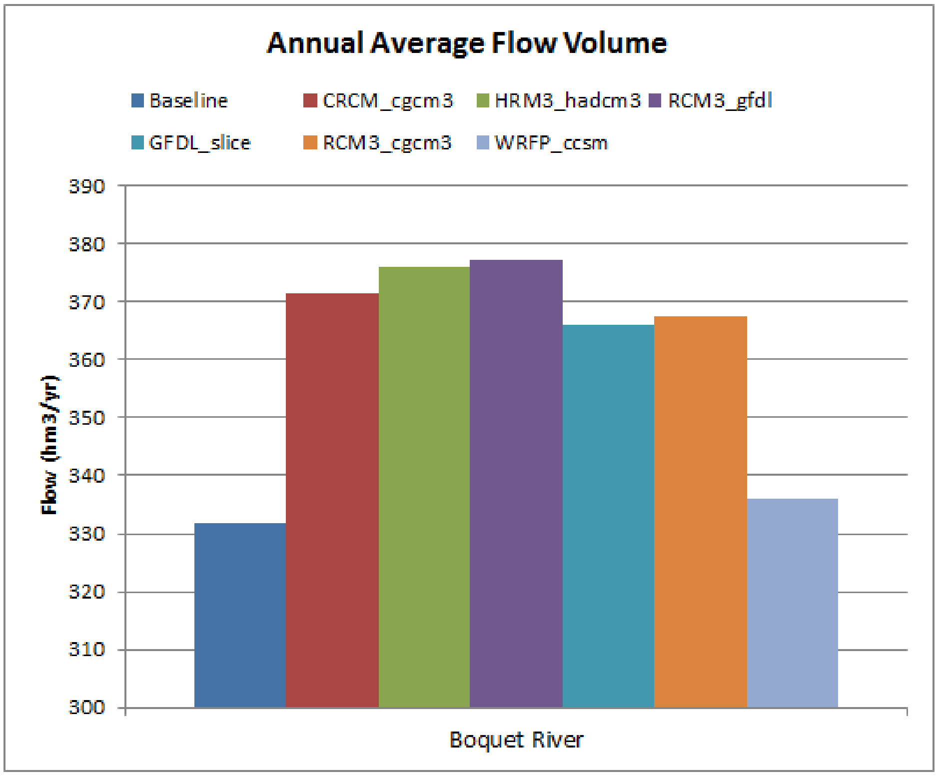


Figure 38. Average monthly flow volume across all NAARCAP scenarios – Boquet River

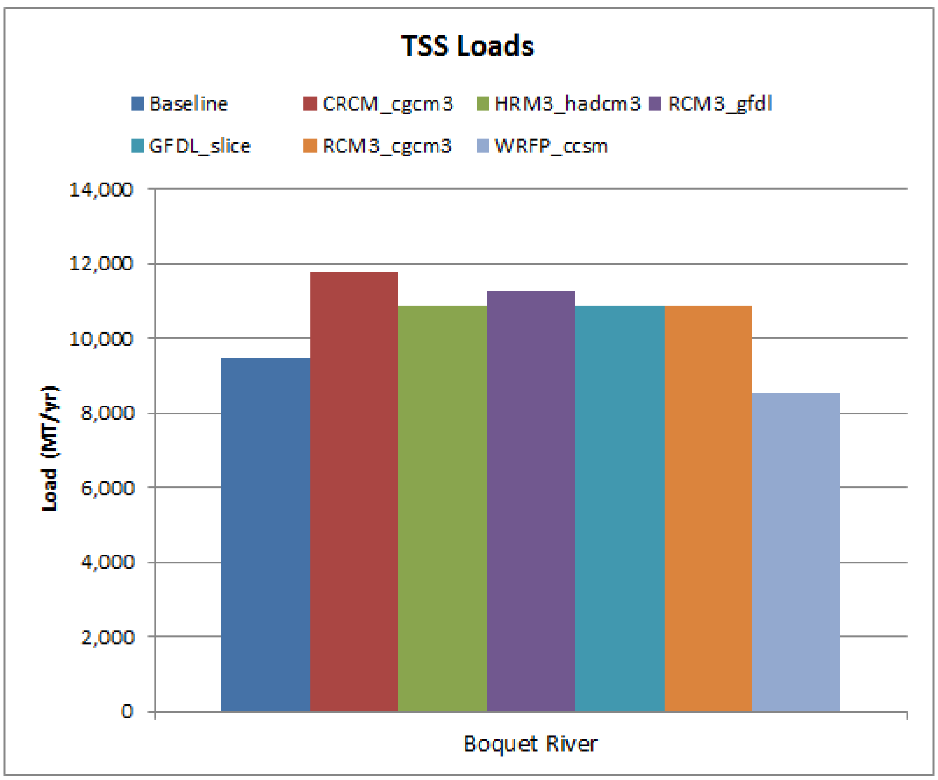


Figure 39. Average monthly TSS load across all NAARCAP scenarios – Boquet River

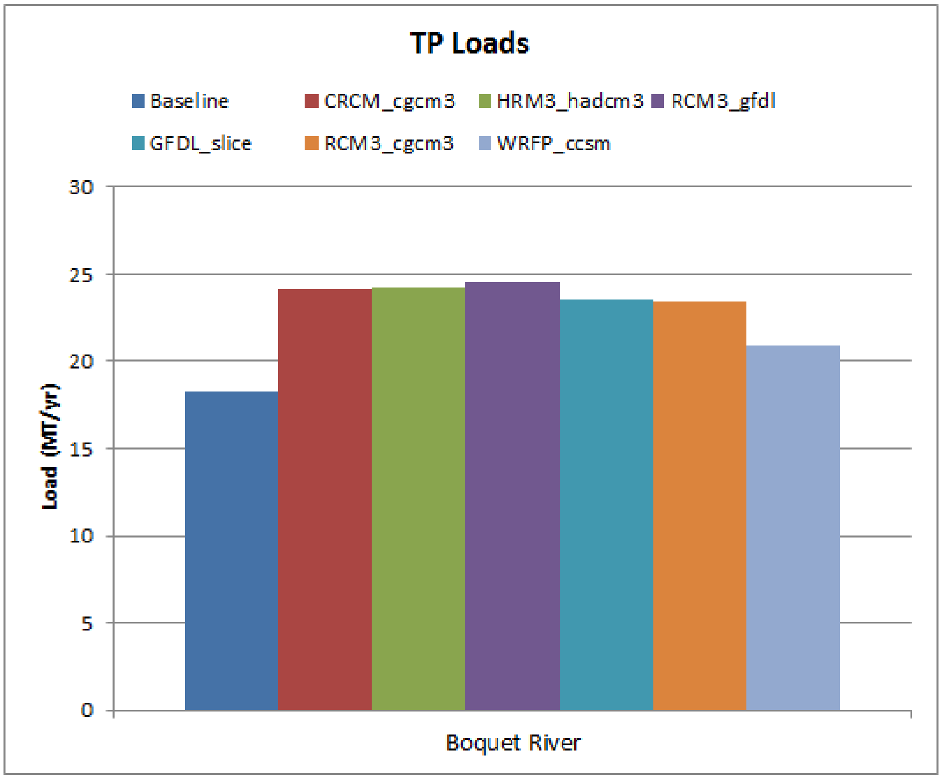


Figure 40. Average monthly TP load across all NAARCAP scenarios – Boquet River

Rock River and Pike River

Table 15. Rock and Pike Rivers - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Rock River				
Flow	18.70%	38.55%	37.24%	48.11%
TSS	26.19%	55.06%	53.81%	73.14%
TP	24.58%	40.04%	38.96%	52.50%
Pike River				
Flow	10.22%	27.72%	26.23%	35.27%
TSS	9.06%	39.22%	35.30%	52.70%
TP	0.55%	15.24%	14.85%	26.72%

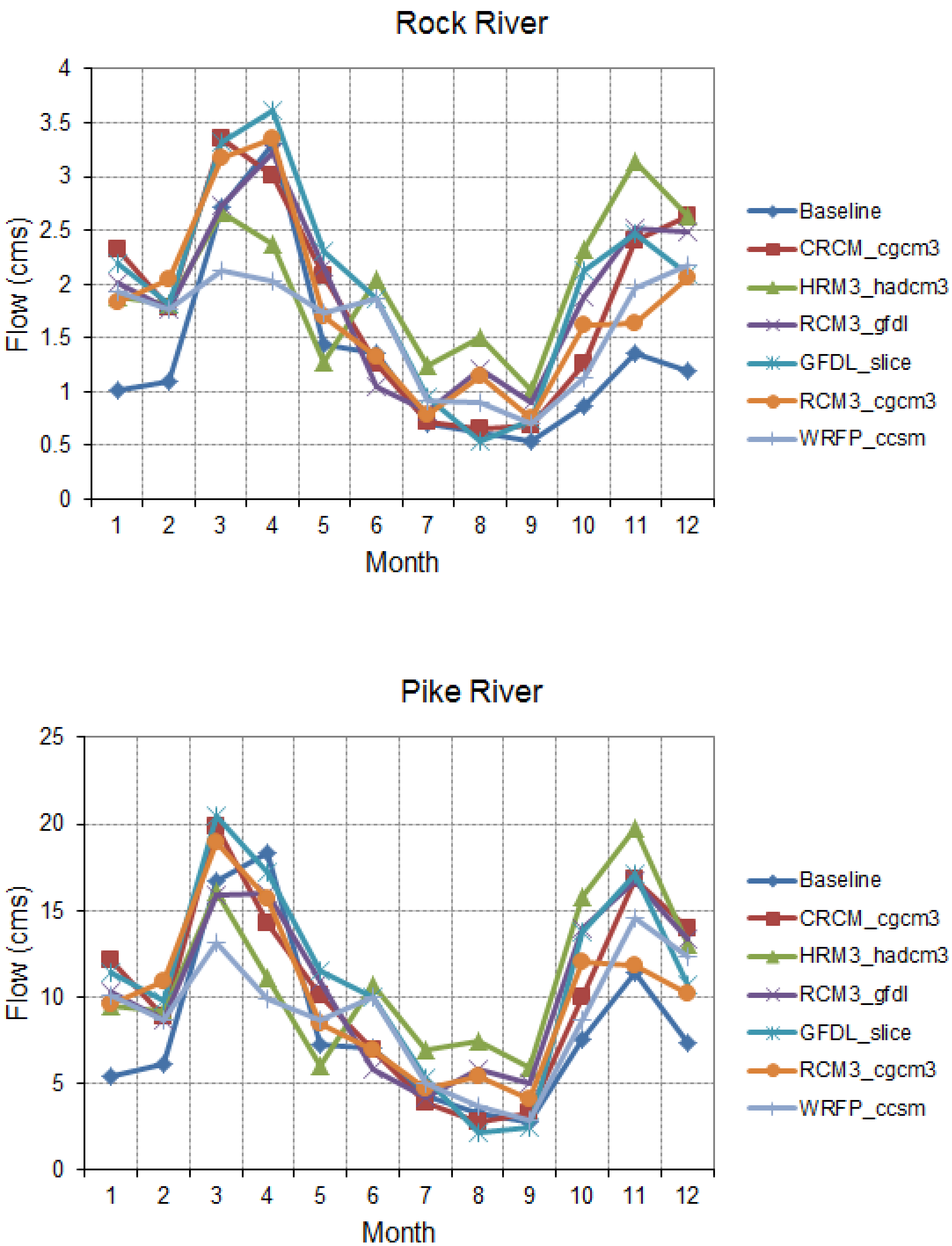


Figure 41. Average monthly flow volume across all NAARCAP scenarios - Rock and Pike Rivers

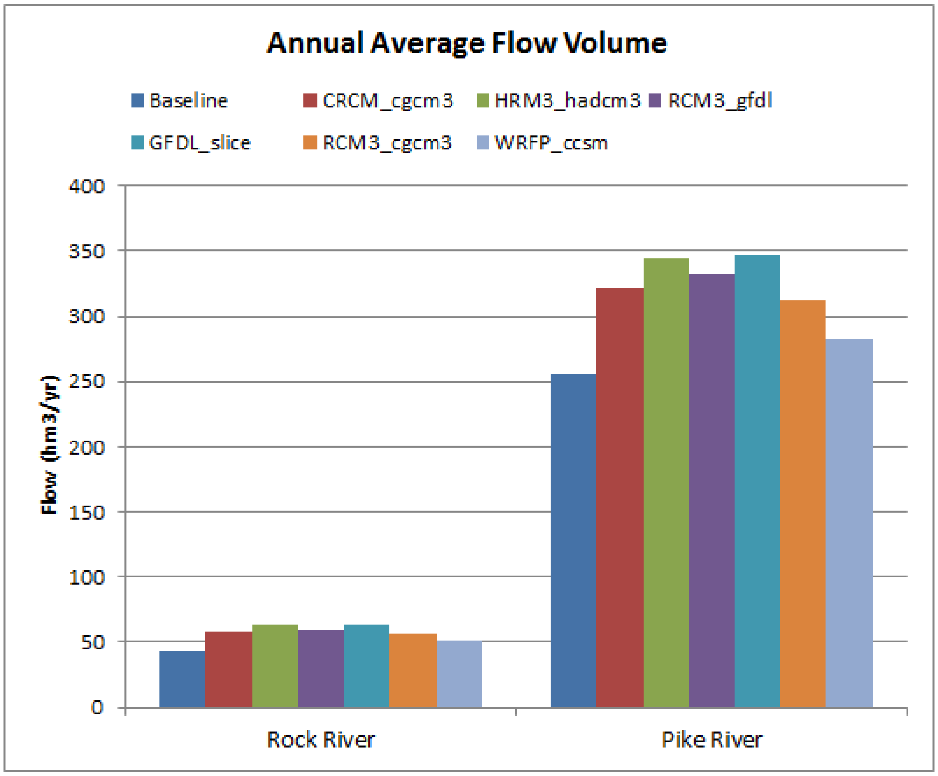


Figure 42. Average monthly flow volume across all NAARCAP scenarios - Rock and Pike Rivers

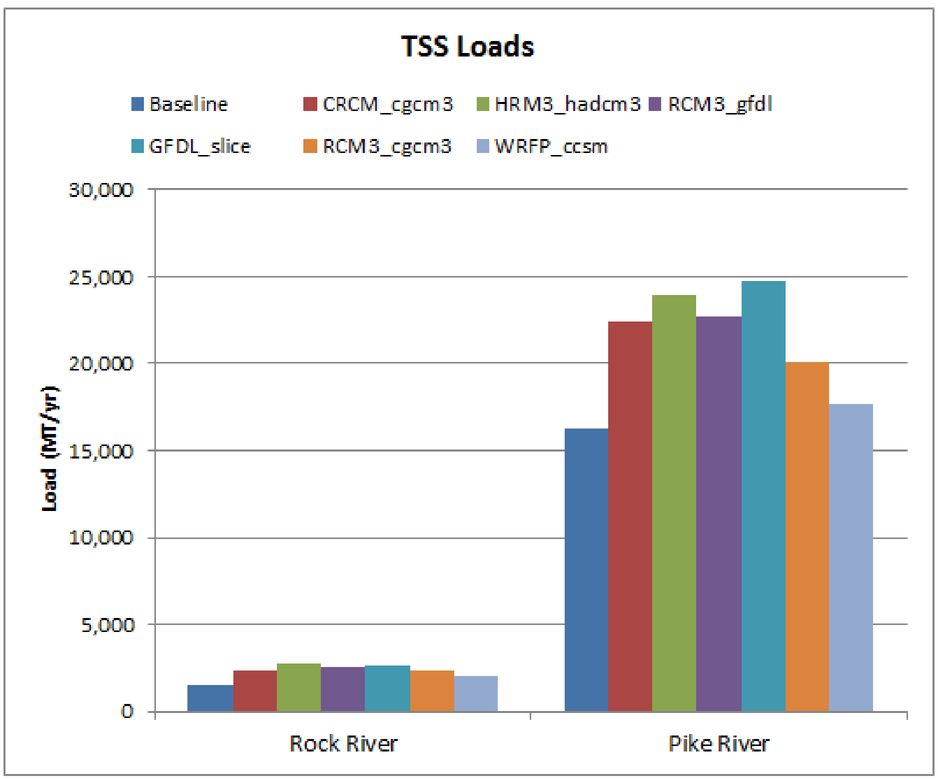


Figure 43. Average monthly TSS load across all NAARCAP scenarios - Rock and Pike Rivers

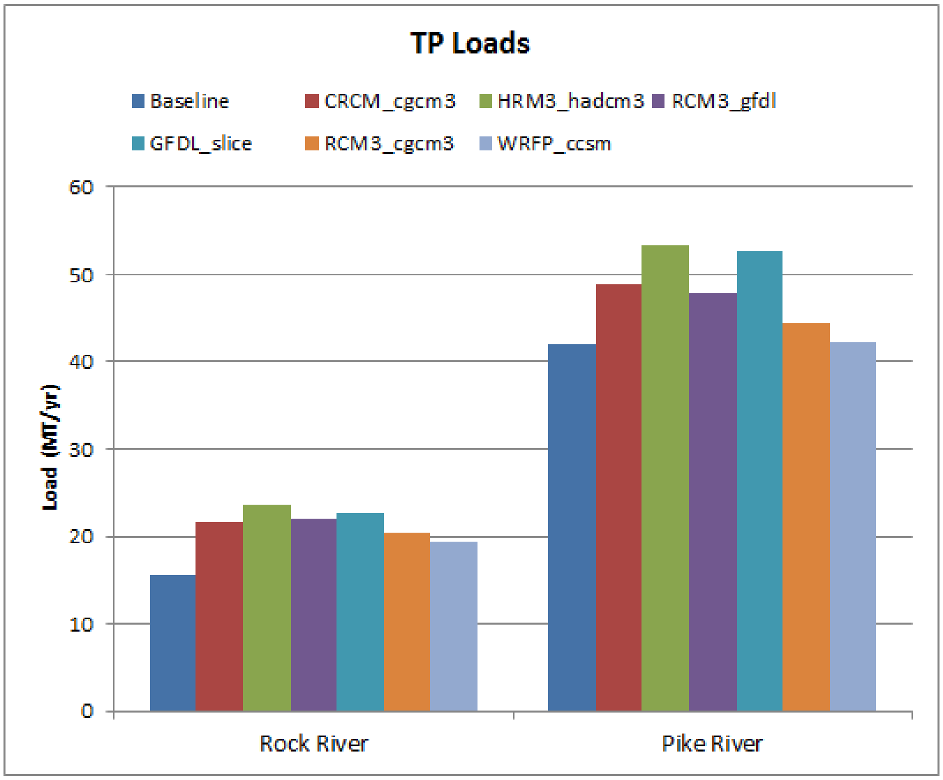
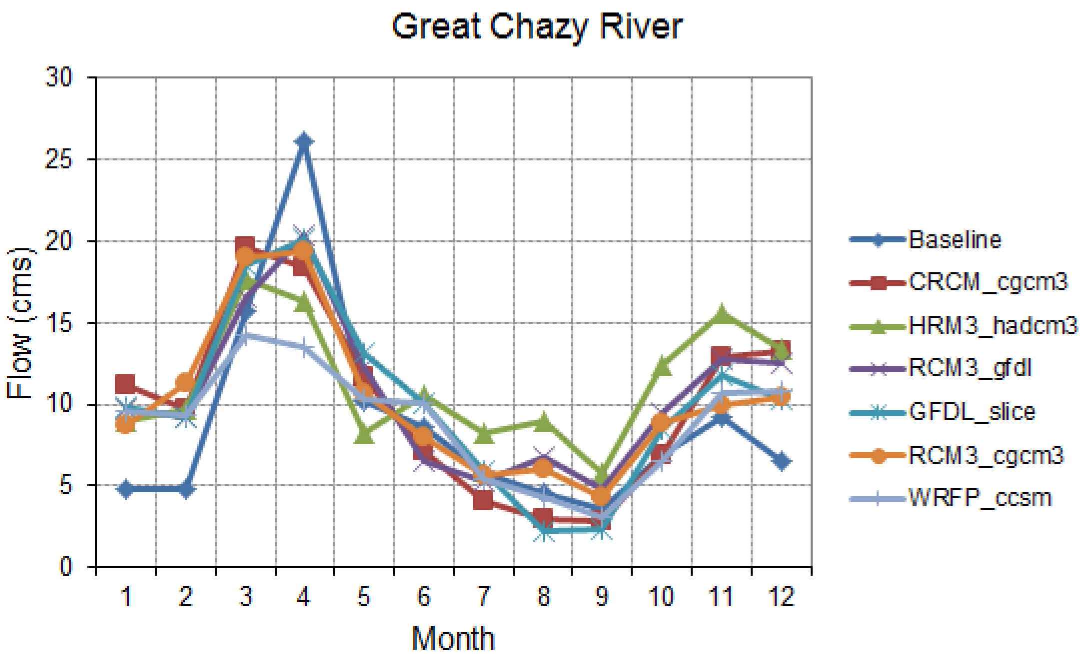


Figure 44. Average monthly TP load across all NAARCAP scenarios - Rock and Pike Rivers

Chazy River

Table 16. Chazy River - Changes in average annual flow and load across all NAARCAP Scenarios

Constituent	Min	Median	Mean	Max
Great Chazy River				
Flow	0.83%	14.19%	14.50%	26.87%
TSS	-9.86%	11.87%	11.02%	25.51%
TP	-1.80%	19.48%	18.78%	40.05%
Little Chazy River				
Flow	-0.76%	15.68%	14.89%	26.10%
TSS	-17.19%	15.27%	14.51%	38.35%
TP	-3.42%	17.50%	19.65%	46.73%



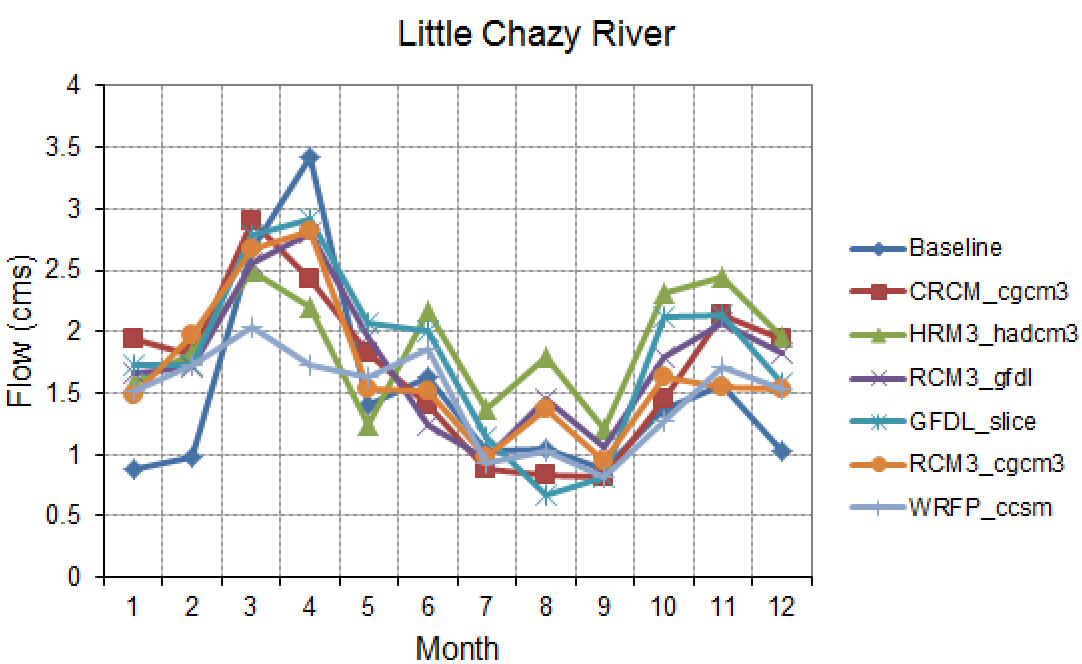


Figure 45. Average monthly flow volume across all NAARCAP scenarios – Chazy River

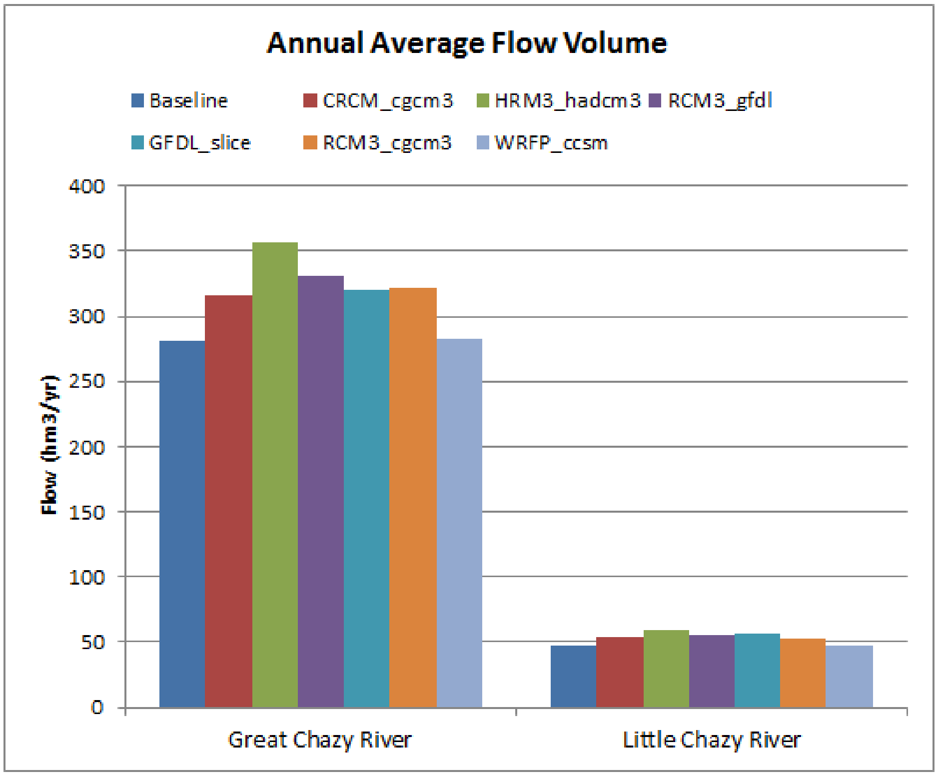


Figure 46. Average monthly flow volume across all NAARCAP scenarios – Chazy River

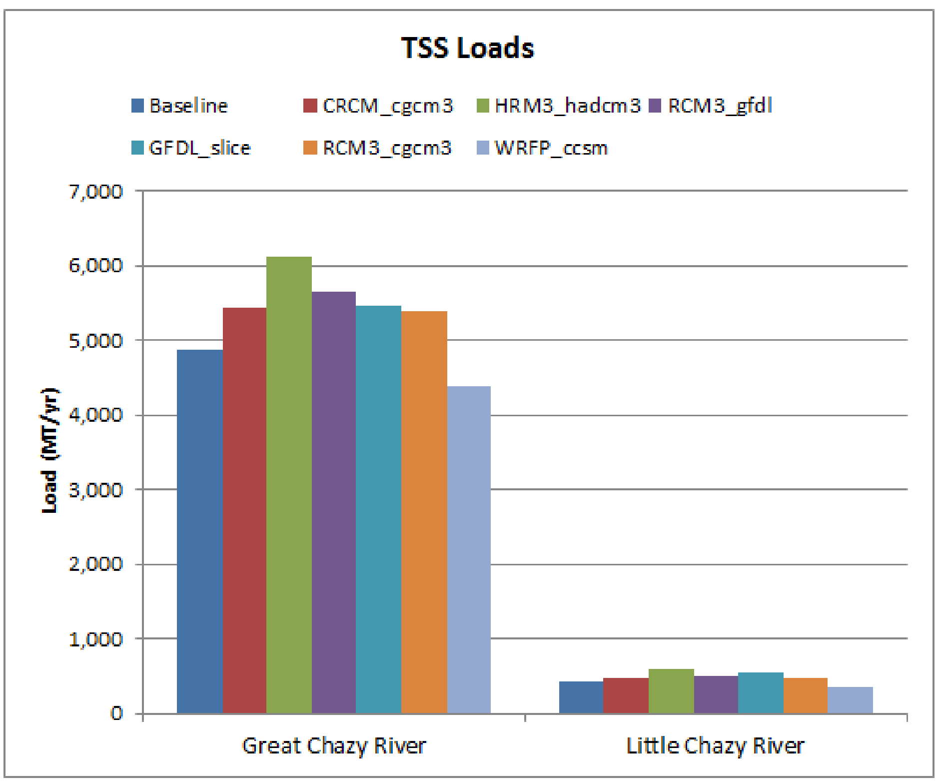


Figure 47. Average monthly TSS load across all NAARCAP scenarios – Chazy River

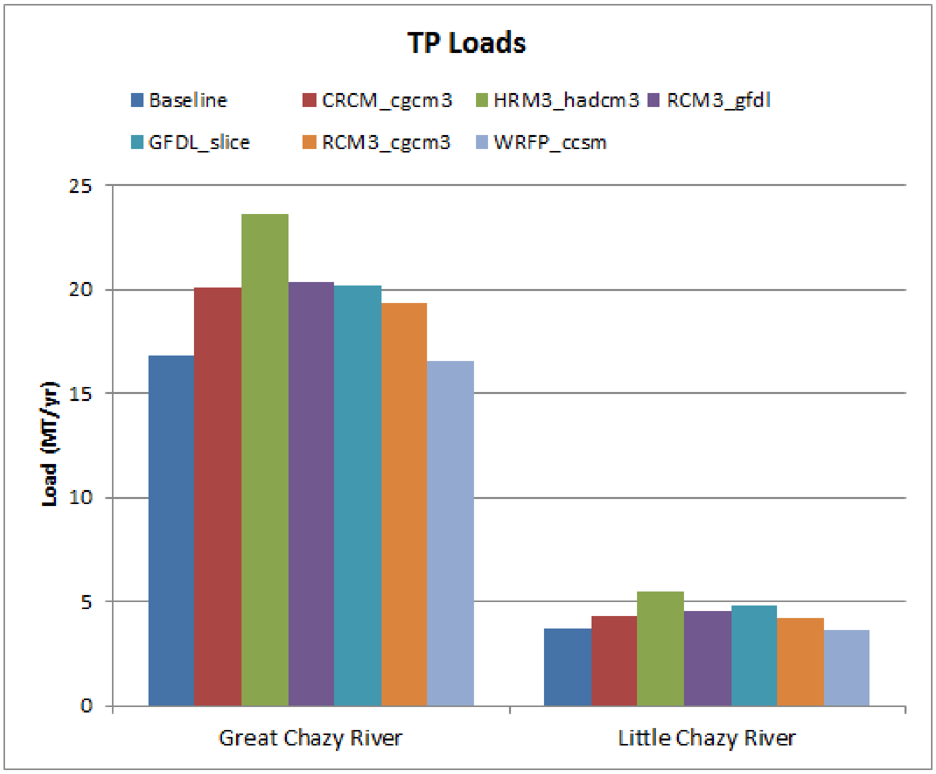


Figure 48. Average monthly TP load across all NAARCAP scenarios – Chazy River

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