EUTROPHICATION OF RESERVOIRS ON THE COLORADO FRONT RANGE

by

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Eutrophication of Reservoirs on the Colorado Front Range

Section I. Executive Summary and Conclusions

Introduction

Eutrophication has been observed in many, if not most, reservoirs along the Colorado Front Range. While eutrophication is a natural process, the rapid pace with which it is occurring in Front Range reservoirs is a cause for concern. In several reservoirs, water quality has already been impacted to the extent that treatability for municipal water supply is affected, and in some cases, recreation and aesthetics have been impacted as well. In addition to taste and odor concerns associated with excess algae production, elevated levels of total organic carbon (TOC) are an increasing concern because of the harmful and strictly regulated disinfection by-products that result from chlorinating waters high in TOC. Management intervention may be necessary across the region for protecting these beneficial uses over the long term.

With few exceptions to date, Front Range reservoirs have been studied individually, and management has been addressed on a case-by-case basis. This approach makes sense in that each system is unique limnologically, and the uses of the reservoir are often primarily local. The disadvantages of this approach are, however, that there are very likely common lessons that could be learned regarding causes, effects, and potential solutions to the eutrophication problem.

Study Description

The study described herein is a regional effort to explore these commonalities, by organizing and synthesizing available background information on twelve case-study reservoirs, all of which provide municipal water supplies to Front Range cities. The reservoirs included in the study are: **Aurora Reservoir, Boyd Lake, Burch Lake, Carter Lake, Horseshoe Lake, Horsetooth Reservoir, Lake Loveland, Marston Reservoir, Quincy Reservoir, Ralph Price Reservoir, Rampart Reservoir**, and **Standley Lake**.

Participants and sponsors of the study include the Colorado Water Resources Research Institute, the Northern Colorado Water Conservancy District, the U.S. Bureau of Reclamation, and the following Front Range municipal water providers: Aurora, Denver Water, Fort Collins, Longmont, and Westminster.

Simply put, the study attempts to answer the following question**. Is a regional approach to monitoring, modeling, and managing Front Range drinking water reservoirs justified?** Since this question does not have a simple answer, the study identifies similarities, differences, and knowledge gaps that are important for developing an answer. The study has three components:

1. a survey of reservoir characteristics, water quality issues and management approaches,
2. an evaluation of existing eutrophication models, and
3. an evaluation of the importance of food web dynamics in determining reservoir water quality.

The survey consisted of a questionnaire that was completed for all of the case study reservoirs except Boyd, Loveland, and Horseshoe. The responses were compiled in an Access database and are summarized later in Section II of this report.

The model comparison involved the application of three existing reservoir models to three of the case-study reservoirs for which data were available. The models included the following:

- Vollenweider model, a simple phosphorus mass balance with assumed P-DO relationship,
- Chapra-Canale model, same as Vollenweider with addition of sediment storage and re-suspension of phosphorus, and
- CEQUALW2, complex multi-purpose reservoir water quality model.

The reservoirs included in the model comparison were Aurora Reservoir, Horsetooth Reservoir, and Standley Lake. The model CEQUALW2 requires a large investment of time for implementation on a given reservoir. Therefore, it was run for Aurora Reservoir only, using model parameters from an earlier study by Hydrosphere. The results of the model comparison are included as Section III.

A general description of how the food web can affect reservoir water quality and a discussion of possible food-web or "top-down" effects on the case study reservoirs is presented as Section IV.

Overall Conclusions

The primary question of interest, that of whether a regional approach to monitoring, modeling, and management of drinking-water reservoirs is justified, cannot be answered fully. While it is clear that commonalities in monitoring will be highly beneficial, it is not clear that a simple and practical modeling approach would have regional applicability. Reservoir management depends highly on local priorities and politics, limiting the feasibility of regional approaches.

To be more specific:

1. Eutrophication and nutrient inputs are the dominant water quality concern of the participating water providers.
2. Most of the case study reservoirs share several important characteristics.
    a. Most rely on water imported from outside the watershed for a major fraction of their supply.
    b. Spring and late summer or fall algae blooms are common.
    c. Anoxic conditions in the hypolimnion are common in late summer.
    d. Most reservoirs appear to be phosphorus limited for most of the year, with possible nitrogen limitation in late summer. Nitrogen limitation may cause blue-green algae (which can fix nitrogen) to become a problem.

3. It follows from the above that management efforts should attempt to reduce phosphorus inputs to the extent that the reservoirs will become phosphorus limited year round.
4. The case study reservoirs differ greatly in their physical characteristics such as depth, age, and retention time.
5. Operational characteristics are highly variable among the reservoirs.
6. Water quality management strategies, including watershed protection and limitations on recreational use, are highly variable among the reservoirs.
7. Since phosphorus is probably the dominant controlling factor for eutrophication, there is at least some potential for a common modeling approach based on a phosphorus mass balance.
8. Of the three existing models that were applied to the case study reservoirs, none provided very good results. Dissolved oxygen in the hypolimnion was modeled more accurately than was total phosphorus.
9. Of the three models studied, the Chapra and Canale model provided the best results considering the level of effort required for implementation. However, the study did not provide a completely fair comparison of model performance since an earlier calibration of the CEQUALW2 model was used.
10. Improved results for the Chapra and Canale model could likely be obtained by further refinements of the model. These include increasing the temporal resolution of the phosphorus inputs and reservoir volume calculations (both assumed constant over the year) and recalibrating the P-DO relationships.
11. Top-down effects of predators on lower trophic levels in food webs may have important ramifications for reservoir water quality but the survey revealed that most sampling programs did not include food web analysis. Therefore, existing data are insufficient to infer which of the study reservoirs may have stronger top-down control over water quality than others. The wide range of reservoir characteristics and water quality exhibited by the study set suggest possible variation in the magnitude of top down control. Studies of Horsetooth and Carter reservoirs have shown that zooplankton abundance and species composition is highly correlated with planktivorous predators, but more work may be needed to determine to what extent phytoplankton and oxygen levels are affected by the food web. In order to assess top-down forces on water quality, each reservoir will need to be examined further on a case-by-case basis to determine linkages between fish and zooplankton population dynamics. Information on phytoplankton abundance and species composition should also be collected and compared to zooplankton and fish populations in trying to assess top-down effects on water quality.
12. Accurate measurement of phosphorus loads to reservoirs and concentrations within reservoirs is important for management, even if a reservoir model is not used. However, phosphorus sampling and analytical methods differ greatly among monitoring programs and laboratories. These differences complicate modeling, setting standards, and measuring standards compliance. Future collaboration among Front Range water providers in the areas of monitoring and modeling can help to provide consistent information to local water managers, regulators and the public.
13. Further research is needed to
    a. improve the simple reservoir quality models in this study and further assess their potential,

b. improve our understanding of trophic relationships in Front Range Reservoirs, including nutrient limitations of algae growth and importance of top-down controls, and
c. further characterize linkages among trophic status indicators and water quality variables that affect water treatment.

Eutrophication of Reservoirs on the Colorado Front Range

Section II. Survey Results

In 2001, as the initial phase of a regional study of Colorado's Front Range reservoirs, Laurel Saito and Marci Koski undertook the task of creating a Colorado reservoir survey, which developed a database of background knowledge on the Front Range Reservoirs of the participating agencies. The data were collected from the appropriate participating agency using a survey questionnaire completed for each reservoir in the study. This database contains data on reservoir physical parameters, monitoring programs, operational characteristics, and the concerns of the reservoir managers and water treatment plant operators as related to water quality. The following material in this chapter will help define some of the commonalities and differences in the Front Range reservoirs.

Due to time constraints faced by City of Greeley staff, the lake survey was not completed for Lake Loveland, Boyd Lake, and Horseshoe Reservoir, and these reservoirs do not appear in all of the figures. The data and background information included here were provided by the City of Greeley in reports from water quality studies of these reservoirs conducted for the City by Lewis and Saunders (2000, 2001, and 2002). Studies of several other reservoirs have been conducted as well and are mentioned only briefly in this section. Those studies are reviewed in Section III of this report.

2.1 I Review of Reservoir Properties

Reservoir physical properties are presented in Table 2.1 and discussed below.

Table 2.1 Reservoir physical properties

Reservoir	Watershed Area (ac)	Surface Area (ac)	Surface Elev (ft)	Volume (Ac-ft)	Max Depth (ft)	Mean Depth (ft)	Age (Years)	Residence Time
Aurora R	2,400	805	5931	31,650	110	39	12	6 Years
Burch L		106		1848			111	
Boyd L		1650		49,048		30		3 years
Carter L		1144	5759	112,230	141	82	50	1.25 years
Horseshoe L		650		7796		12		0.4 years
Horsetooth R	11,000	2040	5440	168,000	180	82.4	50	1.5 years
L Loveland		450		12,738		28		0.4 years
Marston R		621	5538	19,796	62	26	111	<1yr
Quincy R	2,500		5713	2700	38		28	2 Years
Ralph Price R		222	6420	16,197	190	180	30	Weeks
Rampart R			5914	1300	47		34	Days
Standley L	1000	1200	5506	43,000	96	36	92	1 year

Aurora Reservoir

Aurora Reservoir is a mid-size reservoir owned and operated by the City of Aurora. It has a local watershed area of 2390 acres, which historically has been grazed and farmed with 418 acres used for parks and open space. Currently development is underway to change the grazed and farmed land to a school and medium density developments. The small tributaries contribute little total flow to the reservoir but may contribute significant nutrients. Aurora Reservoir became operational in 1990, making it the youngest reservoir in the study at 12 years. Average annual inflows and outflows are small compared to maximum volume, giving Aurora its large, 6 year residence time. Water is entirely used for drinking, but for a majority of the year water does not flow in or out of the reservoir, creating an on-off flow situation not found in most Western reservoirs. Aurora Reservoir and its watershed have been studied by CH2M-HILL, Hydrosphere Resource Consultants, and Black & Veatch.

Burch Lake

Burch Lake is a small reservoir owned and operated by an irrigation company. It has a watershed of unknown size and inflows and outflows are not monitored. It was built in 1891, making it one of the two oldest reservoirs in the survey at 111 years. Water is used for both drinking and irrigation. Major withdrawals occur only in the summer and are for the Wade Gaddis WTP and the Oligarchy irrigation ditch. Burch Lake has seasonal problems with algae blooms in the spring, mid-summer, and late summer, however, the small size and shallow depth of Burch Lake have kept anoxic conditions from developing.

Carter Lake

Carter Lake is a large, deep reservoir, operated by the Northern Colorado Water Conservancy District (NCWCD) as part of the Colorado-Big Thompson System. It has some year-round demand to supply the Carter Lake Water Treatment Plant.

City of Greeley Reservoirs—Boyd Lake, Horseshoe Lake, and Lake Loveland

Boyd and Lake Loveland are mid-size reservoirs, while Horseshoe Lake is small. All three reservoirs are shallow. The three reservoirs are supplied primarily by the Big Thompson River and CBT system, with some input from local drainage. The three reservoirs are connected, providing water to the Boyd Lake Water Treatment Plant.

Horsetooth Reservoir

Horsetooth Reservoir is a large, deep reservoir owned by the Bureau of Reclamation and operated by the Northern Colorado Water Conservancy District. Most of Horsetooth's water comes from the Colorado-Big Thompson (C-BT) diversion from the Western Slope, which enters at the Hansen Feeder Canal. Water is used for drinking by the City of Fort Collins and for irrigation. Horsetooth is a narrow reservoir, with a major axis of approximately 6.7 miles and minor axis of approximately 1 mile. One major cove is present, Inlet Cove, where the Charles Hansen Feeder Canal enters the reservoir. It has a local watershed area of 17.5 square miles, which is primarily to the west of the reservoir and has been occupied by parks and open space with some limited development in Inlet Cove for the past 20 years. Previously the area was in beef cattle grazing. A number of small tributaries contribute little water to the reservoir with spring flows averaging <1 cfs and instantaneous storm flows seldom exceeding 3 cfs (Jassby and Goldman, 1996). Horsetooth was built in 1951 and was the subject of a study by limnologists Alan Jassby and Charles Goldman in 1995-96.

Marston Reservoir

Marston Reservoir is a mid-size, shallow reservoir owned and operated by Denver Water. The reservoir, located in southwest Denver, was constructed in 1891, making it tied with Burch Lake as the oldest reservoir in the study.

Quincy Reservoir

Quincy Reservoir is a small reservoir operated by the City of Aurora. Quincy's four square mile watershed is predominantly urbanized: mainly residential with some commercial development, however the local watershed is now routed into a diversion channel around the reservoir that passes over the emergency spillway. Most of the water in the reservoir comes by pipeline from Rampart Reservoir but it also receives water from the supernatant from the backwash of the Griswold water treatment plant. One item of note is that the reservoir had an aeration system installed in 1997 that prevents the lake from stratifying. This has prevented the lake from going anoxic, but there still are problems with blue-green algae blooms and the associated taste and odors.

Ralph Price Reservoir

Ralph Price Reservoir is a mid-sized reservoir owned and operated by the City of Longmont. At an elevation of 6420 feet, it is the highest reservoir in the study; it is also the deepest reservoir studied. The reservoir fills the St. Vrain River valley and is the only run-of-the-river reservoir in our study.

Rampart Reservoir

Rampart Reservoir is a small reservoir owned and operated by the City of Aurora. The reservoir has large inflows and outflows as compared to its volume, giving it an extremely short residence time

Standley Lake

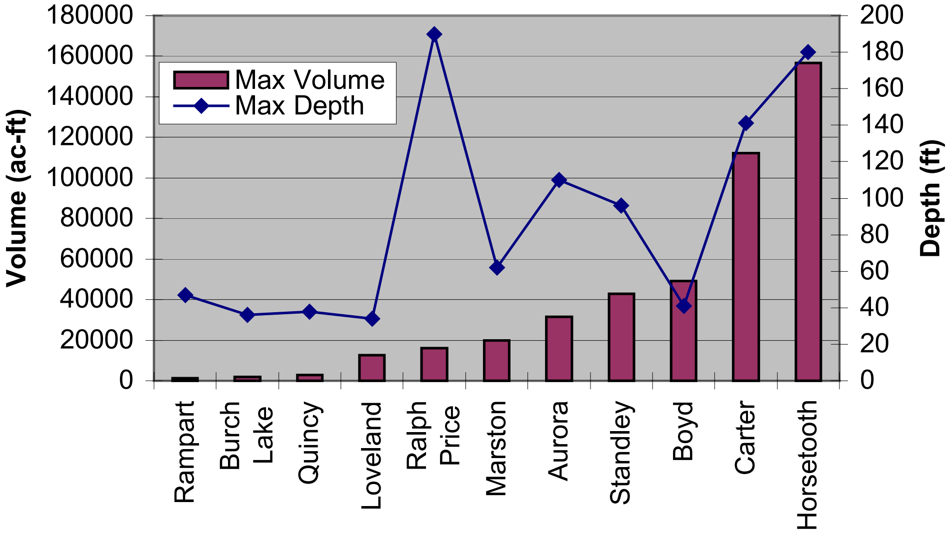
Standley Lake is a mid-size reservoir that provides water to the Cities of Westminster, Thornton and Northglenn. The reservoir is triangularly shaped with sides of approximately two miles and a major cove jutting out of one side. It has a local watershed of approximately 1000 acres. The watershed is in a variety of mixed uses - park and open space, large lot residential, grazing, agriculture, industrial, and commercial, with primary use being open range with grassland. Standley was built in 1910 for irrigation use and was enlarged to its current capacity in 1966 to provide increased capacity for the growing number of municipal users. Natural inflow to the lake is intermittent with a majority of the water coming from Clear Creek and a lesser amount from Coal Creek through one of four canals depending on the time of year. Standley

Lake has been the subject of studies by Richard P. Arber Associates, the United States Geological Survey, and Alex Horne Associates.

2.2 Summary of Reservoir Properties

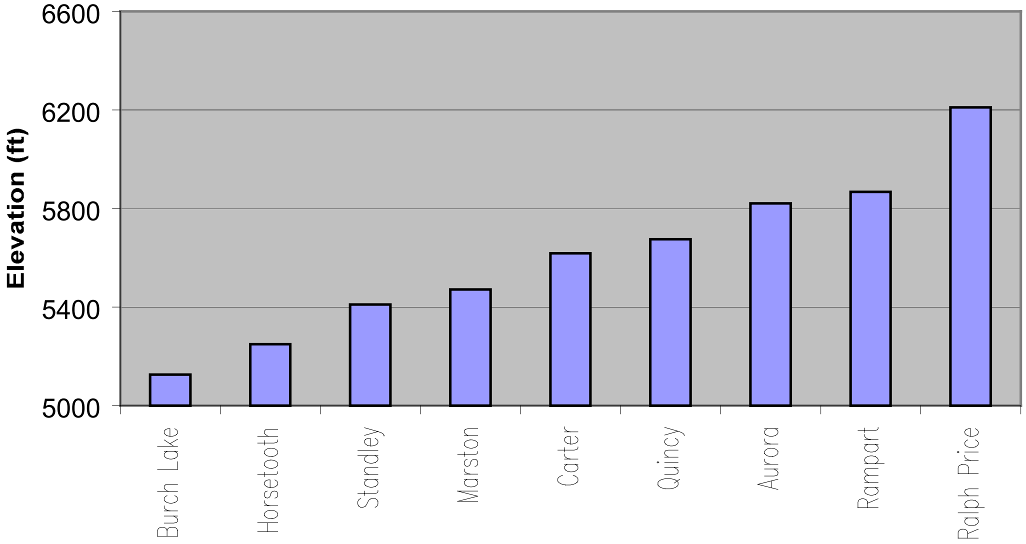
The twelve reservoirs in the study are located along Colorado's Front Range, extending from Fort Collins in the north to just south of the Denver Metropolitan area. The reservoirs in the study range in size over several orders of magnitude (Figure 2.1), with the largest reservoir (Horsetooth) having a maximum volume of over 100 times that of the smallest (Rampart). Three of the reservoirs (Rampart, Burch, Quincy) can be considered 'small' with maximum volumes less than 3000 ac-ft. (Horseshoe Lake at 7,800 ac-ft is not shown in the figure.) Another six (Loveland, Ralph Price, Marston, Aurora, Standley, and Boyd) can be considered 'mid-sized' with maximum volumes between 10,000 and 50,000 ac-ft. The two remaining reservoirs (Carter and Horsetooth) are 'large' reservoirs with maximum volumes over 100,000 ac-ft.

Figure 2.1: Reservoir Volume and Depth



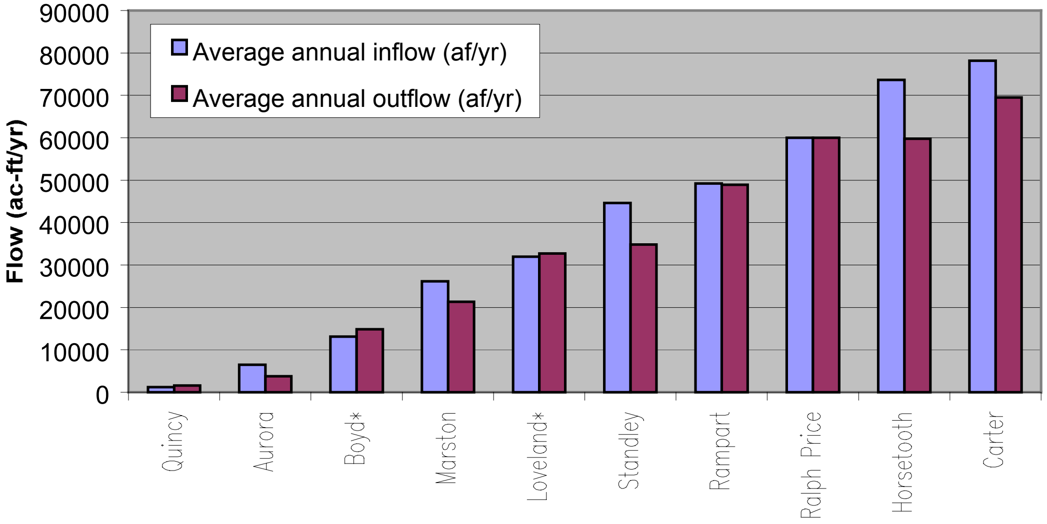
There is a general trend of increasing maximum depth with reservoir volume (Figure 1), with the exception of Ralph Price Reservoir. Ralph Price is very unique in this study, as it is the only run-of-the-river reservoir, and it is also the deepest and highest reservoir. Bottom elevation (Figure 2.2), was noted because it helps illustrate the similar environment of high plains and low foothills occupied by all the reservoirs except Ralph Price, which is in more mountainous terrain that is over 1000 feet higher than the lowest reservoir (Burch) and almost 350 feet higher than the next highest study reservoir (Rampart).

Figure 2.2: Reservoir Bottom Elevation



Average annual inflows over the study period were higher at all reservoirs than average annual outflows (Figure 2.3). Data were not available for Burch and Horseshoe Lakes, and data for Ralph Price Reservoir were estimated from the St. Vrain Creek Drought Study based on average annual streamflow for the North St. Vrain Creek. Flow values ranged from about 1200 ac-ft/yr at Quincy Reservoir to almost 80,000 ac-ft/yr at Carter Lake.

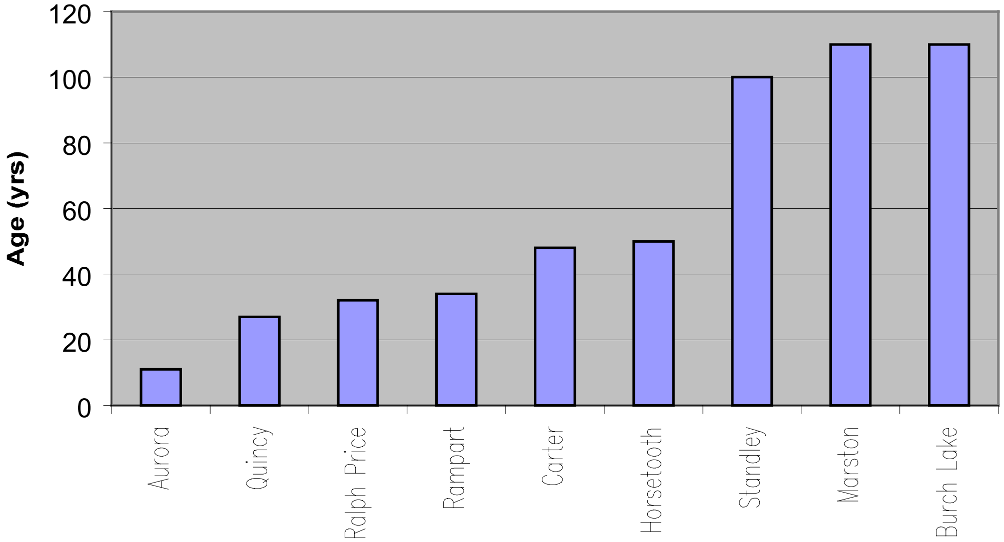
Figure 2.3: Reservoir Inflows and Outflows



* indicates flows Jan-Oct '99

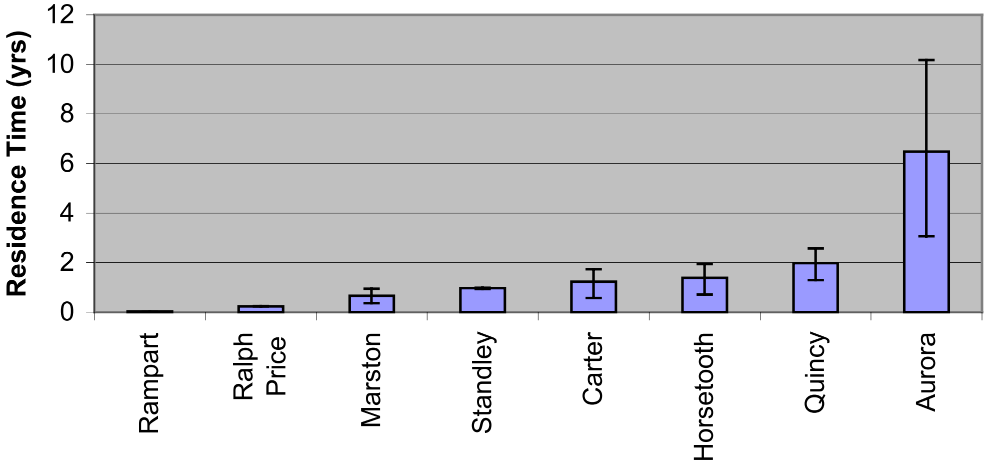
The study reservoirs range in age from 12 years (Aurora) to 111 years (Burch and Marston), with an average age of 58 years (Figure 2.4).

Figure 2.4: Reservoir Age



Reservoir residence times vary significantly between the reservoirs with Rampart Reservoir having a residence time on the order of days and Aurora Reservoir having a residence time in the range of 6 years (Figure 2.5). However, Aurora Reservoir's residence time will likely decrease as the city of Aurora grows and its water demand increases. Residence time can have a significant impact on the amount of eutrophication. As Vollenweider noted, fast flushing reservoirs can maintain higher average TP values with few problems than can slow flushing reservoirs.

Figure 2.5: Average, Minimum, and Maximum Residence Times



2.3 Current Reservoir Standards

The reservoir survey included questions on the type and adequacy of water quality standards at each reservoir. The responses are summarized in Table 2.1. Four of the reservoirs (Rampart, Quincy, Marston, and Burch) have no state-imposed nor site-specific standards, though Quincy Reservoir has water quality goals that are neither formally adopted nor enforceable. The lack of standards at these reservoirs was generally considered "adequate" by the managers, except at Burch Lake, which should ideally have standards for phosphorus and Chlorophyll-a. However, it would be difficult to impose standards on this reservoir because the City of Longmont does not own this reservoir, and its operation and management are dominated by agricultural interests that may not be amenable to imposed standards on the reservoir.

Table 2.1: Summary of responses regarding standards

Reservoir	State-imposed standards					Site-specific	Are standards adequate?
	Aquatic life	Recreation	Water supply	Agriculture	Other		
Aurora		x			See text	See text	Yes
Burch					None	None	No
Carter	Cold I[a]	×[a]	×[a]	×[a]	None	None	Yes
Horsetooth	Cold I	×	×	×	None	None	No
Marston					None	None	Yes
Quincy					None	See text	Yes
Ralph Price	Cold I[b]	×[b]	×[b]	×[b]	None	None	No
Rampart					None	None	Yes
Standley	Warm	×	×	×	See text	See text	No

[a] State-imposed standards are actually for the South Platte River Basin
[b] State-imposed standards are actually for the St. Vrain River

Two other reservoirs (Ralph Price and Carter) do not have any state standards imposed directly on the water in the reservoir, but the water in the reservoirs falls under the standards for the St. Vrain and South Platte River Basins, respectively. The St. Vrain has standards for water supply, agricultural use, and recreation class I, but these standards are not enforced for Ralph Price Reservoir. The section of the South Platte River Basin encompassing Carter Lake is classified as aquatic life cold I, recreation class I, water supply, and agricultural use. There are no other state-imposed or site-specific standards at either of these reservoirs. The standards at Carter Lake were considered to be adequate by the Northern Colorado Water Conservancy District. At Ralph Price Reservoir, the City of Longmont feels that standards should be imposed because it is a drinking water supply, but they should not have difficulty achieving the standards because of the high quality of the water source to this reservoir.

Horsetooth Reservoir is classified as aquatic life cold I, recreation Ia, water supply, and agricultural use. As part of this classification, there is a dissolved oxygen limit of 6.0 mg/L, which is sometimes difficult to achieve at Spring Canyon Dam in the late summer. There are no additional site-specific standards, and the City of Fort Collins does not feel the existing standards are adequate. The City feels that ideally phosphorus standards should be set on the source waters to Horsetooth, and a Chlorophyll-a standard should be set at Horsetooth to protect the reservoir from increased eutrophication.

Standley Lake is classified as aquatic life warmwater, recreation I, water supply, and agricultural use. It also has state-imposed fish ingestion standards that go with the use classifications. There is also a narrative standard at Standley Lake that says that the reservoir must be maintained in a mesotrophic status as defined by a panel of experts. Because of the vagueness of this narrative, the panel has not agreed on a definition of mesotrophy, and the standard has not been enforced. The City of Westminster does not consider the existing standards to be adequate because they feel there should be numeric nutrient limits on Standley Lake and its inflow source (Clear Creek).

Aurora Reservoir is not classified as a drinking water source by the state, but has a state-imposed swim beach standard for E. coli. There are also site-specific water quality goals for Aurora Reservoir. Like those for Quincy Reservoir, these goals are neither formally adopted nor enforceable. As with Rampart and Quincy Reservoirs, the City of Aurora feels the current set of standards and goals are adequate, but realize that at some future date it may be necessary to formalize the site-specific water quality goals and enforce them.

2.4 Current Reservoir Operational Characteristics

Some patterns were seen in the usage of outlets and spillways (Table 2.2). Only three of the reservoirs (Aurora, Marston, and Quincy) had multiple outlets for drinking water supply. (Note that Burch, Carter, and Horsetooth have multiple outlets, but only one outlet is used for drinking water supply.) At Aurora Reservoir releases have historically been made through the top gate unless there were treatment problems, in which case the lower gates were used. In 2001, the City of Aurora started using water from the second gate from the top unless problems occurred. Similarly, at Quincy Reservoir, the top outlet has generally been used unless treatment problems occurred, in which case release was moved to an outlet that provides better water quality. In both 2001 and 2002, the lowest (third) outlet was used. In Marston Reservoir multiple outlets have been used, but there has been no regular pattern in the use schedule.

Table 2.2: Comparison of outlet and spillway usage for study reservoirs

Reservoir	**Multiple outlets?**	**Are all outlets generally used?**	**Is there a spillway?**	**Is the spillway used frequently?**
Aurora	Yes	No	Yes	No
Burch	No[a]	--	Yes	No
Carter	No[a]	--	No	--
Horsetooth	No[a]	--	No	--
Marston	Yes	Yes	Yes	No
Quincy	Yes	No	Yes	No
Ralph Price	No	--	Yes	Yes
Rampart	No	--	Yes	No
Standley	No	--	Yes	No

[a] There are different outlets for different uses, but only one outlet for drinking water supply

Two of the reservoirs have plans to renovate their outlet facilities. Denver Water has proposed to install a new intake tower at Marston Reservoir to change the releases through three gates with similar release capacities (currently, the largest intake is on the bottom of the reservoir). This would allow Denver Water to blend water from the reservoir and a conduit that bypasses the reservoir. This would enable them to: 1) take advantage of the small amount of water going down the South Platte River in low flow times while keeping the plant rate up; and 2) dilute 'poor' quality reservoir water with higher quality river water during times when the reservoir is anoxic. At Standley Lake, a renovation project will add a mid-level outlet. At the time of the survey in 2001, there was hypolimnetic withdrawal only at 15 feet above the bottom of the reservoir.

Spillways are present in all but the C-BT reservoirs (Carter and Horsetooth), but only Ralph Price and Quincy Reservoirs actually use them with any frequency. The spillway on Ralph Price Reservoir is generally used all summer because the City of Longmont keeps the reservoir full during the summer, and it is a run-of-river reservoir. Quincy Reservoir spills rarely--only when it is full, other sources are used to meet demand, or for water quality reasons. However, water from a diversion ditch around the reservoir—carrying runoff from storms and lawn irrigation—also runs down the spillway.

In terms of operations, each of the reservoirs has distinct operating schedules that reflect the size of the reservoir, water quality issues, and coordinated operation of multiple water supplies and/or multiple water uses. Because reservoir operations are often interconnected, operational characteristics are presented according to groups of related reservoirs.

City of Aurora Reservoirs (Rampart, Aurora, Quincy Reservoirs)

Rampart Reservoir receives water from the Strontia Springs Reservoir, which captures water from the East and West Slope via Spinney Reservoir and Elevenmile Reservoir. It has two outlet pipelines: a 54" pipeline to Aurora Reservoir and/or Wemlinger WTP, and a 40" pipeline to the Griswold WTP. The combined capacity of the two pipelines is 74 mgd, and they are interconnected at several points.

Aurora Reservoir is filled in the fall and winter via the pipelines from Rampart Reservoir and well pumping. Withdrawals from the reservoir are treated in the summer at the Wemlinger WTP. Thus far, the City has not treated winter withdrawals, but they expect that they will have to in the future because of degredation in water quality. The fill and release pattern for Aurora Reservoir is limited by the pipeline size from Rampart Reservoir. The pipeline between Aurora Reservoir and Wemlinger WTP can also be used to fill the reservoir. This pipeline is gravity fed to Aurora at flows less than half full, after which it must be pumped. If the water is going to Wemlinger WTP, it must be pumped.

Quincy Reservoir does not have a 'typical' operating pattern. It is filled throughout the year with supernatant from the backwash of the Wemlinger WTP processes. Although there is a channel around the reservoir to direct runoff from the immediate watershed away from the reservoir, it is unlined with areas that are difficult to maintain, so there is likely some leakage and seepage into the reservoir. The water from Quincy Reservoir is treated at the Griswold WTP. The Water Supply and Treatment Division of the City of Aurora operates all three reservoirs (Rampart, Aurora, and Quincy).

Colorado-Big Thompson Reservoirs (Horsetooth Reservoir and Carter Lake)

Horsetooth Reservoir is typically kept low in September and October for maintenance on the inflow canals. In October and November there is a small inflow (<200 cfs), with greater inflow in the winter. The target is to fill the reservoir by May. Carter Lake is filled during the winter months before Horsetooth Reservoir. Demands from Horsetooth Reservoir are supplied throughout the summer. Similarly, at Carter Lake, most of the outflow is during the summer irrigation and high use season, although some municipal releases occur year-round to Carter Lake WTP and to the Southern Water Supply Pipeline. Note that currently Horsetooth Reservoir is being held at 5360 feet due to dam reconstruction over the next several years. Reservoir inflow and outflow operation for both reservoirs is determined by orders placed by the various C-BT and Windy Gap owners, and the inflow and outflow is jointly coordinated by the U.S. Bureau of Reclamation and NCWCD.

Standley Lake

In winter months, 80% of Clear Creek is diverted to Standley Lake. It is also filled during the spring, although the preference is to let the high TOC and high nitrogen concentrations that come in the early snowmelt go by the reservoir. Three cities (Westminster, Northglenn, and Thornton) use the water year-round, with highest usage in the summer (~25,000 ac-ft/yr). There are also irrigation withdrawals from the reservoir in the summer (~5-10,000 ac-ft/yr). The operation of the reservoir is dictated by a 4-way legal agreement between the cities of Westminster, Northglenn, and Thornton, and the Farmers Reservoir and Irrigation Company (FRICO), which represents the irrigation interests.

City of Longmont Reservoirs (Burch Lake, Ralph Price Reservoir)

At Burch Lake, the ditch water right decree comes into effect around January or February and the reservoir is slowly filled under this decree so that it fills by May. The reservoir is kept full through July or August while the ditch water right is in priority. Because of the water right, reservoir operation is determined by the irrigation ditch company. Currently the reservoir is being kept 24 inches below maximum due to safety requirements imposed by the State Engineer's Office. The City of Longmont has deliberately drawn down the reservoir in late summer to force it to turn over for the past couple of years. Ralph Price Reservoir is typically filled by runoff in mid-June, and the City of Longmont keeps the reservoir full until C-BT deliveries are off (around mid-October), when they begin drawing down the reservoir until about mid-April. The State Water Commissioner determines operation of this reservoir.

Marston Reservoir

The preferred operational scenario for Denver Water's Marston Reservoir is to leave the reservoir full during the winter, but lately the reservoir has been low in the winter to allow work in the reservoir such as dredging or construction. The treatment plant at Marston is used all summer and whenever it is needed during the rest of the year. The operation of the reservoir is determined by the

Water Rights Division and executed by the Source of Supply Section in the Operations Division. There are meetings in October and March when everyone involved in the water supply system (including water rights, construction, water planning, and water quality) meets to determine the projected operational schedule.

2.5 Seasonal Water Quality Patterns

Algae blooms were reported at six of the nine reservoirs. The six reservoirs all reported a fall turnover, typically around late September to October. Stratification typically begins around May or June, and several of the reservoirs reported anoxic conditions that appeared around July (Aurora, Marston, and Standley Lake). Manganese was mentioned as a problem or potential problem in three of the reservoirs (Aurora, Horsetooth, and Standley Lake). The seasonal water quality patterns for each reservoir are summarized below:

Aurora Reservoir: Aurora Reservoir becomes anoxic by the end of July and turns over in October. At turnover, phosphorus increases, and there is a spike in algal blooms in October. Algae blooms in the spring are much smaller. Whether or not there is a spring turnover is unclear. The City feels that the water quality degrades every year. Manganese seasonally builds up near the bottom or the reservoir, but so far this has not been a problem for treatment. Occasionally, the City has problems treating water from the reservoir in the spring because it is "too clean", i.e. it does not flocculate properly due to low alkalinity and low suspended solids.

Burch Lake: There are typically several algae blooms, usually in May, June or July, and September. The reservoir does not go anoxic because it is too shallow to stratify, but there is a lot of plant material present. No manganese problems have been observed or reported.

Carter Lake: NCWCD is not aware of any seasonal water quality problems of significance. Water quality can and does change throughout the year, but not to a degree that is noticed by water users.

City of Greeley Reservoirs—Boyd Lake, Horseshoe Lake and Lake Loveland: All three reservoirs have experienced some algae blooms, especially in the fall, including species that are a particular nuisance from a water treatment perspective. Algae problems, along with nutrient concentrations, are the greatest in Lake Loveland , followed by Horseshoe Lake, with Boyd Lake generally having the highest water quality. However, in 2001, Lewis and Saunders found higher chlorophyll concentrations in Boyd Lake than in Lake Loveland.

Although all three reservoirs are relatively shallow, thermal stratification occurs. Anoxic conditions in the hypolimnion and associated phosphorous release from the sediments are a perennial problem in Lake Loveland. Anoxia does occur in Boyd Lake but is less persistent than in Lake Loveland.

Lewis and Saunders (2002) describe the high phosphorus concentrations of the Big Thompson River as a significant concern. They also note that the surface concentrations of nitrate in both Boyd and Loveland reach very low levels in late summer, creating nitrogen-limited conditions that may contribute to problems with blue-green algae that are nitrogen fixers. Nonpoint sources in local drainage may affect water quality of these reservoirs. Lewis and Saunders (2002) stress the importance of controlling both nitrogen and phosphorus inputs to these reservoirs to prevent further degradation of water quality

Horsetooth Reservoir: The reservoir typically turns over once per year. There are few problems when the reservoir is fully mixed. Sometimes there are algae under the ice cover, contributing to sporadic problems with filter-cloggers in January, February, or March. High manganese levels and *Metallogenium* (a bacteria that mats manganese and particles) cause problems that typically appear in July or August and become increasingly severe through October and November until turnover occurs. When dissolved oxygen goes above 2 mg/L, *Metallogenium* is no longer a problem. The reservoir usually turns over around the first two weeks of November unless there is a windy day before then. A spike of turbidity is usually seen at turnover, and manganese problems end. Fluctuations of total organic carbon (TOC) are observed, especially when filling the reservoir from the C-BT project.

Marston Reservoir: The reservoir hypolimnion is usually anoxic by the end of July. The anoxic layer builds up, and Denver Water sometimes has to use the bypass (sends river water straight to treatment plant, not through reservoir) because the anoxic layer exceeds the intake elevations (at least 2 of the 4 intakes - the bottom intake being the largest).

The reservoir has taste and odor problems that correlate with the presence of the anoxic layer, but they are not related to methyl-isoborneol or geosmin, the two most common taste and odor causing contaminants. In the 1980s, there were algae problems at the reservoir, but there are currently no such problems. The reason for this is unknown.

Quincy Reservoir: There is a big problem with algae blooms at this reservoir. The reservoir stratified annually until an aeration system was installed in 1997. There is now a later onset of water quality problems, and the reservoir does not go anoxic. Water quality improvement occurred very slowly after the aeration system was installed. Large blue-green algae blooms continued in early to mid-summer causing taste and odor problems. However in both 2001 and 2002 water quality improvements were dramatic. In 2002, the city was able to extensively utilize Quincy Reservoir as a high-quality source.

Ralph Price Reservoir: There are no water quality problems other than that the water sometimes is "too clean" to properly flocculate.

Rampart Reservoir: The reservoir has low alkalinity, algae blooms, and some problems associated with runoff. Because of its extremely short residence time, water quality issues at Rampart are largely related to the quality of water coming in from Strontia Springs Reservoir. However, in 2002 the City of Aurora observed unexpectedly high quality of water in Rampart, given the influx of nutrients following the Hayman fire. They surmise that degradation did not occur as long as Aurora used this source extensively, resulting in a very short residence time. Later in the year when more water was used from other sources and the residence time in Rampart was increased, algal blooms were observed.

Standley Lake: The reservoir becomes anoxic during the end of every summer causing manganese problems. The cities' treatment plants combat this problem with potassium permanganate. A $35 million renovation beginning in 2002 should improve some of the water quality problems. The reservoir is typically stratified from May or June through late September. The reservoir becomes anoxic around July and stays anoxic until turnover. Lake overturn occurs in late September due to the removal of the coldest water via the outlet pipe. There is typically a spring algae bloom that depletes the oxygen in the reservoir throughout the summer and a fall bloom due to summer storm pulses of nutrients and nutrient incorporation from the sediments (Horne, 1993).

2.6 Current Reservoir Management Issues

In the survey questionnaire, thirty-one issues were rated for nine of the reservoirs as follows: 0 = not a concern; 1 = a slight issue; 2 = a moderate issue; and 3 = a severe issue. The issues were then ranked in order of importance by calculating a composite score for each concern that was determined as follows:

Composite score = $n_0(0) + n_1(1) + n_2(2) + n_3(3)$

Where n_0 = number of reservoirs rated 0 for this issue

n_1 = number of reservoirs rated 1 for this issue

n_2 = number of reservoirs rated 2 for this issue

n_3 = number of reservoirs rated 3 for this issue

The highest ranked issues were those that were rated as a concern at all nine reservoirs (Table 2.3). Almost all of these were related to eutrophication and reservoir trophic status. Sediment issues and changing water use demands were rated as a concern for all but one of the reservoirs, although the latter issue was rated as a slight concern for half of the reservoirs. Only five issues were rated as being some type of concern for less than half of the reservoirs, including hypoxic conditions, regulatory compliance, institutional issues, agricultural impacts, and fire management.

Table 2.3: Issues ranked by composite score (maximum possible score = 27)

Issue	Composite score	Number of reservoirs rated as 1 slight issue	2 moderate issue	3 severe issue
Nonpoint source pollution	22	2	1	6
Nutrient loading	22	2	1	6
Watershed protection	22	1	3	5
Eutrophication/trophic status	20	3	1	5
Algae blooms	20	2	3	4
Taste/odor	19	0	2	5
Anoxic conditions	18	1	1	5
Sediment issues	18	1	4	3
Urban development	16	2	1	4
Changing water use demands	15	4	1	3
Nutrient limitations	14	3	1	3
Multiple use management	14	3	1	3
Recreational use	13	3	2	2
Point source pollution	12	4	1	2
Upstream waste discharges	12	2	2	2
Fishery management	12	4	1	2
Managed public access	12	1	4	1
Grazing impacts	11	1	2	2
Water rights conflicts	11	3	4	0
Restricted public access	11	0	4	1
Mixing patterns	10	4	3	0
Water level fluctuation	10	4	3	0
Inorganic vs. organic turbidity	9	5	2	0
Exotic species	9	4	1	1
Waterfowl impacts	9	5	2	0
Fire management	9	1	1	2
Impacts of trace metals	8	3	1	1
Agricultural impacts	7	0	2	1
Institutional issues	7	1	3	0
Regulatory compliance	7	2	1	1
Hypoxic conditions	1	1	0	0

2.7 Current Reservoir Fishery Status

Within the study reservoirs, Horsetooth Reservoir has the most diverse community of fish, with 13 species. (Table 2.4) Two of the reservoirs (Burch Lake and Rampart Reservoir) had no fish data available. Rainbow trout were present in all but

Marston Reservoir and are stocked annually or more often. Walleye are stocked once a year or less, with other species stocked as needed. Creel surveys have been done in three of the reservoirs (Carter, Ralph Price, and Horsetooth); informal surveys are done at Aurora Reservoir. Fish surveys have been done at all reservoirs, mostly to look at population trends and determine stocking schedules. The Colorado Division of Wildlife collects all data except at Ralph Price Reservoir, where Longmont does the creel surveys.

Table 2.4: Summary of fish species in study reservoirs. Feeding guilds are: PL = planktivore, PI = piscivore, BE = benthivore.

	Reservoir						
Species (feeding guild)	**Aurora**	**Carter**	**Horsetooth**	**Marston**	**Quincy**	**Ralph Price**	**Standley**
Black crappie (PL/PI)	×				×		
Bluegill (PL)	×		×				
Brown trout (PI)	×	×	×			×	
Carp (BE)			×	×			×
Channel catfish (BE)	×						
Emerald shiner (PL)			×				
Green sunfish (PL/BE)		×					
Kokanee salmon (PL)		×					
Largemouth bass (PI)	×	×		×	×		
Longnose sucker (BE)						×	
Rainbow trout (PL/BE)	×	×	×		×	×	×
Shad, includes gizzard shad (PL)			×				×
Smallmouth bass (PI/BE)	×		×		×		×
Splake (PI)		×				×	
Spottail shiners (PL)	×		×				×
Sticklebacks (PL/BE)	×						
Tiger muskies (PI)			×		×		
Walleye (PI)	×	×	×	×			×
White sucker (BE)		×	×	×			×
Wipers (PI)	×	×	×				×
Yellow perch (PL/PI)	×	×	×		×		×

2.8 Current Reservoir Water Uses

All of the nine reservoirs for which the questionnaire was completed are used for drinking water, with a five of the reservoirs (Burch, Carter, Horsetooth, Ralph Price, and Standley) also supplying water for irrigation (Table 2.5). In addition, Ralph Price has a portion of its pool used for flood control, and it, along with Carter Lake, supplies water for hydropower. On the recreational side, three of the reservoirs (Carter, Horsetooth, and Standley) allow motorized and non-motorized boating, and three other reservoirs (Aurora, Quincy, and Burch) allow nonmotorized boating. Three reservoirs (Aurora, Carter, and Horsetooth) allow swimming, and the previous three plus three more (Standley, Ralph Price, and Quincy) allow public access to the reservoir. Seven of the reservoirs (all except Rampart and Marston) allow fishing and one (Horsetooth) is a site for fish egg production. Two reservoirs (Standley and Ralph Price) are designated as wildlife sanctuaries and three (Carter, Horsetooth, and Standley) allow camping at the reservoir.

Table 2.5 Reservoir Use Summary

Use	**Reservoir**									**Total**
	Aurora	Rampart	Quincy	Standley	Horsetooth	Ralph Price	Carter	Marston	Burch Lake	
Drinking Water	Y	Y	Y	Y	Y	Y	Y	Y	Y	9
Irrigation	N	N	N	Y	Y	Y	Y	N	Y	5
Flood Control	N	N	N	N	N	Y	N	N	N	1
Hydropower	N	N	N	N	N	Y	Y	N	N	2
Motorized Boating	N	N	N	Y	Y	N	Y	N	N	3
Nonmotorized Boating	Y	N	Y	Y	Y	N	Y	N	Y	6
Swimming	Y	N	N	N	Y	N	Y	N	N	3
Public Access	Y	N	Y	Y	Y	Y	Y	N	N	6
Fishing	Y	N	Y	Y	Y	Y	Y	N	Y	7
Ice Fishing	Y	N	N	N	N	N	Y	N	N	2
Fish Egg Production	N	N	N	N	Y	N	N	N	N	1
Wildlife Sanctuary	N	N	N	Y	N	Y	N	N	N	2
Camping	N	N	N	Y	Y	N	Y	N	N	3

Consideration of a reservoir's designated water uses is important, as the uses often limit the ways in which a reservoir can be managed. Both drinking and irrigation water require large flows from the reservoir during the summer, amounts that are often larger than the inflow during these periods, requiring a drawdown of the reservoir surface and a corresponding decrease in the hypolimnion volume, increasing the rate at which DO concentrations decline. In drought years, of course, the effects of reservoir drawdown will be more pronounced than normal. As discussed later in Section III, the simpler modeling approaches included in this study do not account for the effect of storage changes on hypolimnetic oxygen demand.

Flood control requires the maintenance of some excess reservoir capacity and hydropower requires a year-round supply of water from the reservoir. Recreational uses, such as swimming, boating, fishing, and wildlife sanctuaries, require that a minimum reservoir elevation be maintained to make these uses possible.

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Section III. Colorado's Front Range Reservoirs – a Regional Investigation of Eutrophication Modeling (M.S. Thesis by Brian Gelder)

Abstract of Thesis

Colorado's Front Range has been one of the fastest growing regions in the United States, providing the majority of Colorado's population increase from 2.2 million to 4.3 million in the past 30 years. This growth has created serious water quality problems as watersheds become more developed and the reservoirs that store the water switch focus from providing irrigation water to drinking water. These problems are the result of eutrophication, or excessive algal and plant productivity due to high nutrient loads. Directly, this excessive algae growth clogs filters and causes taste and odor in treated water. Indirectly, the death, sinking, and decomposition of this excessive algal and plant growth creates low dissolved oxygen in the hypolimnion, which mobilizes phosphorus, further enhancing the high nutrient concentrations, and mobilizes manganese, and iron, chemicals that can cause problems for treatment processes.

Typically attempts at monitoring, modeling, and managing the eutrophication problem have focused on a single reservoir. It is proposed, however, that an effort that looks at multiple reservoirs along the Front Range can elucidate some similarities between the reservoirs and allow a uniform and effective monitoring, modeling, and management scheme to be employed to improve water quality. In order to achieve these goals, a survey of 12 Front Range reservoirs including Aurora Reservoir, Boyd, Burch, Carter and Horseshoe Lakes, Horsetooth Reservoir, Lake Loveland, Marston, Quincy, Ralph Price, and Rampart Reservoirs and Standley Lake was conducted to determine physical characteristics, normal operating procedures, and water quality concerns.

After reviewing models previously applied to the reservoirs and reviewing other commonly applied eutrophication models for predictive ability of Total Phosphorus (TP) and Dissolved Oxygen (DO). These constituents are the primary cause and effect of water quality concerns that surveyed reservoir operators and managers were found to have. Relatively simple models by Vollenweider and by Chapra and Canale were then calibrated for TP and validated at Aurora and Horsetooth Reservoirs and Standley Lake using yearly average data to evaluate the ability to model the constituents of concern and the models' ease of use. To enable comparisons with more complex models, a previously calibrated CE-QUAL-W2 model of Aurora Reservoir was also run. Time constraints limited the application of the CE-QUAL-W2 to this instance.

In contrast with the observed TP data, the Vollenweider model did not predict any seasonal cycling. Both the Chapra and Canale and CE-QUAL-W2 models predicted the appropriate seasonal cycling in TP, but the timing was slightly off in both models. Regardless of cycling, all three models had similar difficulty predicting the daily TP concentration. Each model produced Root Mean Square Error values that were at least 33% and typically 75% of the mean whole-reservoir observed TP for the time period. A comparison of the mean whole-reservoir predicted TP with the mean whole-reservoir observed TP for the calibration and validation time periods was somewhat more favorable, with the Vollenweider and the Chapra and Canale predicting values within 15% of what was observed. The CE-QUAL-W2 performed similarly; the predicted mean whole-reservoir TP was off by 20% but the RMSE was slightly better. Although not calibrated for DO, all three models were more effective at daily DO prediction, producing RMSE values that were about 25% of the mean observed DO concentration.

The similar TP modeling results and the ease of model implementation lead to the recommendation of the Vollenweider and the Chapra and Canale models over the provided CE-QUAL-W2 model for TP and DO modeling. Use of daily, weekly, or monthly input and reservoir parameters may increase the accuracy of the Vollenweider and the Chapra and Canale models, further enhancing benefits. However, the Vollenweider and the Chapra and Canale models are not suitable for all reservoirs in the Colorado Lakes Survey, as Rampart Reservoir has an extremely short (~1 week) residence time, invalidating the fully mixed assumptions of the models.

Finally, a decision tree was developed to aid in determination of modeling feasibility and appropriateness based on reservoir characteristics and availability of time and funding.

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CHAPTER 1.0 INTRODUCTION

Eutrophication, or enhanced productivity in a water body due to increased nutrient input (Chapra, 1997), of Colorado's reservoirs has been a concern since the 1970s (EPA, 1976), and these concerns have continued to the present day. These reservoirs made Colorado's semi-arid landscape suitable for large-scale agriculture and the accompanying human population, providing drinking and irrigation water, flood control, and power generation. However, the growing population along the Front Range has shifted the focus of many reservoirs from irrigation water to drinking water, and eutrophication creates conditions that limit the use of the water for drinking more than for irrigation. These conditions are the result of the fact that increased nutrient input creates conditions under which algae can grow to unsustainable populations, die off, and then bloom again. The decomposition of this organic matter creates a reducing, low oxygen condition that can dissolve many metals, create unpleasant odors, and cause numerous water treatment problems.

1.1 Background and Scope

Several of the reservoirs along the Front Range that were included in this study were constructed for irrigation water in the late 1800s to mid 1900s when the Front Range was primarily a collection of farms and rural agricultural communities. The biggest concerns with irrigation water were quantity and salt content of the water. For irrigation supply, nutrients levels are generally not of concern, and high levels may even be considered desirable, as their presence decreases the need for fertilizer. Algae blooms, although unsightly, were not a major concern as their presence did not significantly limit the water's irrigation potential.

Management emphases have now shifted from irrigation to drinking water for many Front Range Reservoirs. This creates problems as reservoirs used for irrigation water have different management priorities than drinking water reservoirs. Drinking water needs to be more pure, as it has tighter standards, such as Maximum Contaminant Levels for nitrates, NO_3^-, manganese, Mn, and iron, Fe. Algal blooms also create problems by contributing taste and odor to treated water, clogging intake filters, and exacerbating the production of disinfection by-products, DBPs, such as methanohalogens, that are created when organic material is oxidized by chlorine.

These goals are made even more challenging by the fact that Colorado's population explosion in the last half century dramatically increased the populations living in the mountainous areas that serve as the source water for most of the Front Range reservoirs. These increased populations have increased the nutrient inputs to the rivers and streams of the area through fertilization of lawns and agricultural areas and through the treated sewage discharge streams high in phosphorus and nitrogen (Horne, 1993).

These increased nutrient loads raise the fertility of the impoundment, increasing the rate and amount of growth of plant material over that which is sustained by the normal supply of nutrients. This often produces a large variety of algae and cyanobacteria, or blue-green algae, in addition to rooted aquatic plants. The algae grow like any plant, removing nutrients from the water in order to produce cell material. As they live, they add O_2 (Dissolved Oxygen, DO) to the water through photosynthesis and remove DO through respiration. The large supply of nutrients allows the algae to grow to population levels as one of three things occurs: depletion of DO levels during the night, self-shading, or depletion of nutrient levels below that needed for survival. The dead algae are no longer buoyant and begin a descent to the hypolimnion, or lower stratified layer, of the waterbody.

In the hypolimnion, aerobic bacteria decompose this organic material by chemical oxidation. This decomposition uses the dissolved oxygen in the water to proceed, decreasing the levels as the process proceeds. If the amount of oxygen required to oxidize the organic material exceeds the amount of oxygen present, anoxia, or a condition of low dissolved oxygen, occurs. Anoxic conditions are chemically reducing, allowing the mobilization of Mn and Fe, and release of PO_4 from bottom sediments, which helps maintain high fertility levels. The above consequences of eutrophication result in the water treatment problems encountered described above.

There are multiple ways to control the problems associated with eutrophication, all of which include limiting the amount of organic matter decomposition through herbicides, harvesting, or growth limitation. In drinking reservoirs, only growth limitation is a feasible option. This is typically accomplished by limiting nitrogen or phosphorus loads to the reservoir, which decreases the amounts available to the algae and plants to carry out cell maintenance and growth, limiting reproduction.

A common method of assessing eutrophication is the TSI, or Trophic State Index, which can be predicted from chlorophyll-a, total phosphorus, or Secchi depth. TSIs less than 30 suggest oligotrophic waters that do not have problems with anoxia, from 30-40 suggest mesotrophic waters that can have anoxia develop, but the anoxic period is likely not severe enough to cause problems. TSIs from 40-50 suggest eutrophic waters that have anoxic periods long enough to cause Fe, Mn, and odor problems, and TSIs greater than 50 indicate hypereutrophic waters that experience severe problems due to anoxia. Further detail into eutrophication theory and processes can be found in Harper, 1992.

These changes in both watershed makeup and reservoir water management and use have led to the current eutrophication problems we now face. Up to the present, this problem of eutrophication of Front Range reservoirs has been handled on a local watershed basis, meaning that each reservoir was usually studied individually, or if operated as a system of reservoirs, as a small system. This rationale makes sense in that each reservoir is limnologically unique and its contributing watershed is geologically and anthropogenically unique, creating a one-of-a-kind set of circumstances under which each reservoir operates.

However, there are often commonalities between reservoirs in a limited geographical area that, when analyzed, may present solutions to the problem that are not readily apparent or may be more cost effective than when implemented on a single reservoir. To remedy this problem, a team of researchers at Colorado State University, including Dr. Jim Loftis, Dr. Laurel Saito, and Dr. Brett Johnson, Ms. Marci Koski, and the author of this thesis, along with cooperating Front Range water management agencies, have undertaken a regional approach to understanding this problem. Cities currently involved in this study include: the City of Aurora, Denver Water, the City of Fort Collins, the City of Longmont, the City of Greeley, and the City of Westminster. Other water management agencies currently involved in this study include: Colorado Water Resources Research Institute, Northern Colorado Water Conservancy District (NCWCD), and the U.S. Bureau of Reclamation. This has given us access to data on a wide range of reservoirs in the Front Range from Fort Collins to the southern Denver Metro area including: Aurora Reservoir, Boyd Lake, Burch Lake, Carter Lake, Horseshoe Lake, Horsetooth Reservoir, Lake Loveland, Marston Lake, Quincy Reservoir, Ralph Price Reservoir, Rampart Reservoir, and Standley Lake.

1.2 Approach

To date, this joint research approach has produced two main products: a database of reservoir properties and operational characteristics and a survey of reservoir operators' concerns for their reservoirs. To further address the research goals, this thesis endeavors to conduct a review of possible model analyses for predicting the effects of changes in reservoir and watershed management. Two different approaches to modeling and managing the systems are being explored: a top-down approach that investigates piscine and zooplankton control of algal communities, and a bottom-up approach that investigates management of nutrient loads to the reservoirs resulting in growth limiting control of the algal population. This thesis will discuss only the issue of bottom-up approach of management through investigation of suitable models for eutrophication management. Top-down management and control of eutrophication is discussed separately in the project report. Analysis of the monitoring schemes conducted by the agencies involved is also planned in assisting the agencies to implement a cost effective monitoring program that enables effective change detection and model implementation. The database of reservoir properties and table of operator concerns have already revealed many commonalities that will prove invaluable in the completion of the project.

In pursuit of these goals, this thesis will first delve into a review of current knowledge on eutrophication, a review of possible computer models and their outputs, and a selection of possible models. Next will come an overview of current reservoir characteristics, previous modeling efforts and their results, and selection of reservoirs for modeling. Following will be results of modeling on the selected reservoirs. Next are recommendations for computer modeling presented in the form of decision trees for selecting appropriate models for a reservoir. The thesis will then close with a summary of major findings.

CHAPTER 2.0 REVIEW OF PREVIOUS RESERVOIR STUDIES

Analysis of current and past monitoring activities from the Colorado Lakes Survey has revealed three reservoirs that have datasets suitable for reservoir simulation via modeling, Aurora and Horsetooth Reservoirs and Standley Lake.

The first of these reservoirs to receive attention was Standley Lake, a reservoir that stores water for the cities of Westminster, Thornton, and Northglenn. Problems with high manganese levels and algal taste and odor problems first led to an extended study by Richard P. Arber Associates on water quality correlations and trends. The second study period, 1989-1990, consisted of monitoring of loads and algal evaluation by the U.S. Geological Survey. Alex Horne Associates then evaluated the algal communities and trophic state of Standley in 1993 and developed a model to predict changes in water quality accompanying changes in nitrogen and phosphorus loading.

The second reservoir to receive considerable attention was Aurora Reservoir, a reservoir for the City of Aurora. It was the focus of modeling by CH2M HILL during the reservoir assessment (1986) and build (1990) phase. It has since been the subject of studies by Hydrosphere in 2000 due to taste and odor problems and Black & Veatch in 2001 due to concerns about watershed development.

The third reservoir to receive attention by outside consultants was Horsetooth Reservoir, a reservoir managed by the NCWCD that serves as a City of Fort Collins water source. Manganese problems, an indicator of anoxic conditions, were first noticed in the reservoir in 1989 (Alexander, 2002). The continuation of these problems led to a study conducted by Jassby and Goldman (1996).

2.1 Review of Previous Studies

2.11 Summary of Richard P. Arber Associates Study of Standley Lake

Standley Lake was the subject of this study (Paulson, 1986 and Lorenz, 1987) because of concerns about high manganese and algae levels contributing to taste and odor problems in the reservoir. Summer stratification and conditions of low hypolimnetic DO were correlated with manganese being released, and as the period of anoxia increased, manganese levels also increased, corresponding nicely to theory. It was also stated that further depletion of hypolimnetic DO would likely result in increased manganese release and possibly iron and other associated metal releases.

Analysis of algal related taste and odor events revealed a linkage to algal counts, indicating that taste and odor problems could be effectively predicted by monitoring the counts. Algal counts were related to nutrient levels, but it was also noted that there was an inverse relationship between algae growth as measured by chlorophyll-a and outflow volume, indicating that hydrodynamics can also exert an influence on algal counts. Major blooms were noted to occur in the spring (March and April) and the fall (September, October, and November), the periods before and after summer stratification. Algal bioassay studies performed on the lake in 1982 indicated that algal growth was limited by phosphorus early in the year and by nitrogen and phosphorus later in the year.

2.12 Summary of USGS Study of Standley Lake

Ruddy et al. (1992) and Meuller and Ruddy (1993) reported a summary of the water quality measurements taken by the USGS in the 1989-90 conducted to determine loads to Standley Lake. Primary findings include an estimate of the total nitrogen and phosphorus loading to the reservoir from inflow and sediment release, with it being noted that only about 20% of the phosphorus in the inflow water was in the orthophosphate form. Also, nearly all the nutrients released from the bottom sediment occurred during the stratified periods. All algal bioassays showed that addition of both phosphorus and nitrogen was required to increase algal biomass, but all cultured algae failed to produce earthy or musty odors.

2.13 Summary of Alex Horne Associates Study of Standley Lake

The Alex Horne (Horne, 1993) report begins with analysis of the current trophic status of Standley Lake. Mesotrophic and, at times, oligotrophic behavior are indicated by the moderate to low levels of chlorophyll-a in the summer, low Trophic State Index (TSI) using TP, and brief period of high water clarity in the summer. Eutrophic status is indicated by low water transparency during most of the ice-free season, a large spring phytoplankton bloom, high nutrient concentrations and inputs in the winter-spring period, low dissolved oxygen concentrations in the hypolimnion in summer, and high TSIs based on water clarity and modified chlorophyll-a values. Standley Lake seems to have both nitrogen and phosphorus limitations, depending on the time of year. Nitrogen limitations predominate in the fall, whereas phosphorus limitations predominate in the spring and summer.

According to Horne (1993), the chlorophyll-a values for Standley as measured by the USGS are not directly comparable to those obtained by most other methods. The USGS uses a High Pressure Liquid Chromatography (HPLC) step to purify the chlorophyll-a, and it is theorized that this step removes chemicals that are normally measured as chlorophyll-a, resulting in readings that are typically ½ to 1/3 of those obtained by other labs. Horne then adjusts the levels accordingly for his model runs to obtain results comparable to those obtained by Horne's lab.

If one wants to control the amounts of nutrients entering the reservoir, it is helpful to know the sources. For Standley, a majority of the nutrients enter the reservoir in the winter when water is diverted from Clear Creek via the Croke Canal. Clear Creek is the receiving body for a number of septic and wastewater treatment plants and, hence, has elevated levels of TIN (Total Inorganic Nitrogen), NO_3, TP, and PO_4 in the winter because of low flows. Typically at the end of the fall, Standley Lake is low in these nutrients, but the reservoir volume and inflows combine in a 3:1 ratio, respectively, that provides a nutrient rich environment when the reservoir becomes productive the next spring. A natural experiment on the effects of these inputs was carried out in the winters of 1983 through 1985 when Clear Creek was not diverted into the reservoir because of a dispute about the discharge of Coors Brewery waste into Clear Creek above the Croke Canal diversion. During the following summers, DO in the hypolimnion averaged 1.0 mg/L compared with 0.3 mg/L for the other years in the period from 1981 to 1990.

The Horne model predicted that phosphorus or nitrogen loadings must be reduced at least 30% to produce noticeable effects on the dissolved oxygen in the hypolimnion. Reductions in nitrogen loadings are predicted to have a slightly larger impact than reductions in phosphorus loading. The model predictions aligned closely with some of the results obtained when the Clear Creek water was not diverted into the reservoir during the winter. These years amounted to a decrease in the loadings of 100%, and the DO values observed during the summers of 1983 and 1984 aligned with model predictions of

90% reduction in phosphorus load. However, in 1985 model predictions of 2 mg/L did not agree with data, as 0 mg/L DO was observed.

2.13.a An observation regarding the Arber and Horne Studies

Horne (1993) reports that there is a lack of direct correlation between nutrient levels and algae blooms in Standley Lake, although Richard P. Arber Associates (Paulson, 1986 and Lorenz, 1987) indicated there was a correlation. A plausible explanation for this discrepancy is that the bottom outlet of Standley Lake was removing the hypolimnetic high nutrient water from the reservoir during Horne's study period, possibly reducing the correlation between nutrients and algae blooms. Records were not available to determine whether this was the case.

2.14 Summary of CH2M HILL Studies of Aurora Reservoir

A water quality study was conducted during the planning of Aurora Reservoir, as described in the Senac Dam and Reservoir Preliminary Studies Summary (CH2M HILL, 1986b) and the Environmental Assessment for Senac Dam and Reservoir (CH2M HILL, 1986a). As these studies were purely theoretical in nature, they will not be detailed here. The last CH2M HILL (Sorenson, 1990) study, however, was an as-built update to those purely theoretical studies. Using a Canfield-Bachman (1981) model, the study predicted that the reservoir would be classified as slightly eutrophic under normal operating conditions and mesotrophic to slightly eutrophic under interim operating conditions (lower inflow and outflow totals). Both classifications would meet nutrient-related water quality goals for drinking water and recreation. The study did recommend that a watershed water quality management plan be adopted in addition to the City of Aurora Surface Drainage Water Quality Control Criteria that were in effect in 1990 to prevent the potential adverse effects of nutrients and other pollutants originating in the watershed. It also recommended that a complete biological cycle be developed to enhance recreation and water quality, with emphasis on fish species that can survive substantial reservoir drawdown in the late summer-fall.

2.15 Summary of Hydrosphere Study of Aurora Reservoir

Aurora Reservoir was the subject of a study by Hydrosphere Resource Consultants (HRC) during 1999-2000 (HRC, 2000b). The object of this study was to develop a model of water quality (i.e. algae, dissolved oxygen, soluble reactive phosphorus, nitrate, ammonia, organic matter, and inorganic suspended sediments) that could be used as a management tool. Such a tool could help deal with taste and odor problems such as those experienced in the summers of 1998 and 1999. There might have been other times during which similar conditions occurred, but because Aurora is not continuously used as a drinking water source, these periods could go unnoticed.

The beginning of the report dealt with data analysis. Of interest is the fact that both phosphorus and nitrate loads to the reservoir decreased significantly throughout the period of record (1995-1999). The data on surface levels of total nitrogen and total phosphorus lead one to believe that the reservoir is phosphorus limited as the ratio was often above 20:1. A trophic state evaluation revealed some similarities with Horsetooth, as Aurora Reservoir was also a eutrophic reservoir by only some of the definitions. The whole-lake mean annual total phosphorus levels of 22 ug/L placed Aurora Reservoir at the very low end of eutrophic conditions. Chlorophyll-a whole-lake mean annual values of 1.75 ug/L and mean summer values of 1.2 ug/L along with a mean summer Secchi depth of 4.5 m suggested an oligotrophic lake. Both values were well below what would be expected on the basis of TP levels. However, on the basis of DO, which is a key concern in reservoirs used for drinking water, Aurora is without a doubt a eutrophic lake as it undergoes anoxic conditions every year in the late summer-early autumn before overturn replenishes dissolved oxygen in the hypolimnion.

HRC selected the CE-QUAL-W2 model because of its ability to model multiple constituents and its extensive successful use throughout the country. To implement the model, HRC divided the reservoir horizontally into 20 zones encompassing the main reservoir body and all four coves and vertically into 10-foot depth increments. For their study, HRC modeled temperature along with the following constituents: algae, chlorophyll-a, dissolved oxygen, soluble reactive phosphorus, total phosphorus, nitrate, ammonia, organic matter (dissolved and particulate), and inorganic suspended solids.

To calibrate the model, detailed bathymetric data were required along with inflow data from Rampart Reservoir, City of Aurora Wells, East Cherry Creek Valley Wells, direct precipitation, watershed runoff, and outflow data to the water treatment plant. Surface constituent monitoring data from 1995 to September 1999 (the time at which model development began) and bottom constituent monitoring data (collected 1-m above the reservoir bottom) were used along with temperature profile data for calibration.

The report (HRC, 2000b) states that:

> "Simulation results closely match observations for phosphorus, nitrogen, chlorophyll *a*, dissolved oxygen, total organic carbon, and surface temperature. Reservoir bottom temperature values during the July through September periods of 1997 and 1998 were underpredicted for reasons unknown at this time."

Also, the model was not used to predict improvements in anoxic conditions with changes in loadings but did do a good job of estimating the period of hypolimnetic anoxia.

2.16 Summary of Black & Veatch Study of Aurora Reservoir

In response to the impending development of the Aurora Reservoir watershed and recommendations of the CH2M HILL (1990) study, Black & Veatch (Knoll, 2001) attempted to define the maximum allowable phosphorus load that can enter the reservoir while still maintaining water quality as determined by Secchi depth, Chlorophyll a, iron and manganese concentrations, and Areal Hypolimnetic Oxygen Demand, AHOD. This study utilized an empirical loading model developed by Rast, Jones, and Lee (Rast et. al, 1983) to predict TP from average reservoir values and loads from 1997. The predicted TP concentration was then used in Chlorophyll *a*, AHOD, and Secchi Depth correlations also given by Rast, Jones, and Lee (Rast et. al, 1983). The loading equation is given below:

$$P = \frac{\frac{\left(\frac{L}{z}\right)}{\tau}}{1+\sqrt{\tau}} \tag{2.1}$$

Where

P = Total Phosphorus concentration (ug L^{-1})

L = Total Phosphorus loading rate (mg P m^{-2} yr^{-1})

z = mean reservoir depth (m)

τ = hydraulic residence time (yr)

Load sources to Aurora Reservoir include gauged and ungauged runoff, geese, and atmospheric deposition. Of these load sources, the only source easily managed is ungauged runoff, and model predictions indicate this source would have to be limited to 100 pounds of TP annually to obtain the trophic state goals of the reservoir.

2.17 Summary of Jassby and Goldman Study of Horsetooth Reservoir

Horsetooth Reservoir was the subject of a limited resource study by Jassby and Goldman (1996) during 1995. This study evaluated source water management as a response to the appearance of nuisance manganese concentrations that were above the secondary MCL of 50 ppb, causing treatment problems. They used a combination of chemical, physical and biological monitoring data to determine trends and their possible causes in the reservoir. Nuisance manganese concentrations were observed only when the dissolved oxygen in the hypolimnion decreased below 5 mg/L, with an increase in manganese observed with further decreases in DO. This is as would be expected from the reducing conditions present with low DO waters. Similar low DO conditions always appear in the late summer-early fall period.

Data on the current trophic status of Horsetooth from the three monitored locations (Inlet Bay, Dixon and Soldier Canyon Dams) indicates the highly complex nature of the multi-basin system we are dealing with. Using the Carlson Trophic State Index, we find varying diagnoses, with Secchi TSIs usually in the high 40s to low 50s, chlorophyll-a TSIs in the mid 30s to mid 40s, and TP TSIs in the mid 30s to low 40s. The average of the values suggest a TSI of 45, which is in the middle of the mesotrophic range. This suggests that it should be feasible to improve Horsetooth water quality, since it is easier to reduce the period of anoxia through nutrient load reduction in a mesotrophic reservoir than in a eutrophic reservoir.

TSI values also suggest that the lake is phosphorus limited as TP TSI values are lower than chlorophyll-a TSI values 12 times out of 16. This is also supported by data from 1989-94 at the Olympus Tunnel leaving Lake Estes, which feeds Horsetooth, where

16 TN:TP ratios had a mean of 39, with only 3 less than the 25:1 volumetric ratio that is considered the lower bound for phosphorus limitation. These findings would indicate that the most successful way to decrease autocthanous carbon loading (biomatter produced inside system) would be to decrease the phosphorus loading.

Jassby and Goldman (1996) selected the Vollenweider model to test changes in TP loading through source limitation and reservoir management because of the limited resources of their study and the lack of monitoring data. They fine-tuned the model by changing the calibration parameters to predict the current mesotrophic state of the reservoir. This required changing the calibration parameters by varying amounts, up to 75%. They then used the new calibration parameters to predict the effects of four different management scenarios at the lake. Options one and two were 50% and 75% reductions in phosphorus loading from the Feeder Canal. Options three and four consisted of maintaining the water pool at maximum elevation with no reduction and 50% reduction of current loads. The model indicated that maintaining the water pool at maximum elevation should have a positive effect on DO values in the hypolimnion because it increases the volume of the hypolimnion and the total amount of oxygen available in this layer, delaying the time it takes to consume the DO in the layer. The actual benefits may not be as great as those realized through the model, however, as the prediction assumes that organic matter is decomposed equally throughout the hypolimnion, while in actuality most decomposition occurs at the sediment interface. Changing the hypolimnion volume will not affect the anoxic zone near the sediment, and if this interface is the manganese source, the change will likely not be as great as predicted.

The key equations used in this model are:

$$P = \frac{-1 + \sqrt{(1 + 0.4 \times c_1 \times \tau \times P_i)}}{0.2 \times c_1 \times \tau} \tag{2.2}$$

(steady-state solution of Vollenweider's model)

$$B = 0.28 \times c_2 \times P \tag{2.3}$$

$$VHOD = \frac{c_3 \times 240 \times \sqrt{B}}{z_h} \tag{2.4}$$

$$N = (T_f - T_i) - \left(\frac{10^\wedge 3 \times (DO_i - DO_o)}{VHOD} \right) \tag{2.5}$$

Where

P = TP concentration (ug L^{-1})

τ = Hydraulic residence time (yr)

P_i = Inflow phosphorus concentration (ug L^{-1})

B = Chlorophyll-a concentration (mg L^{-1})

$VHOD$ = Volumetric Hypolimnetic Oxygen Demand (mg L^{-1} d^{-1}), a measurement of oxygen demand in the hypolimnion during stratification

z_h = Mean depth to hypolimnion (m)

T_i = Julian day when DO begins to decline linearly (d)

T_f = Julian day when Mn falls below nuisance levels (d)

DO_i = Mean hypolimnetic DO on day Ti (mg L^{-1})

DO_o = Mean hypolimnetic DO at which nuisance Mn begins (mg L^{-1})

N = number of days of nuisance Mn conditions (d)

c_1 = TP sedimentation constant

c_2 = steady-state biomass constant

c_3 = VHOD constant

The model was calibrated by Jassby and Goldman without large changes in the initial values, the largest change that was required was 75%, which, according to Jassby and Goldman, is within the expected range. These changes have plausible explanations: TP sedimentation constant (c_1) greater than 1.0 may be due to the high turbidity, steady state biomass (c_2) lower than 1.0 may be due to the same high turbidity, and the VHOD constant (c_3) greater than 1.0 could be explained by the combination of the large allocthonous carbon load (biomatter produced outside system) measured at the Inlet Canal and the fairly long residence time over which this carbon can further decompose. Measurement indicate this load is of the same order of magnitude as the autocthonous carbon load (produced within system).

The model run used two different start dates, T_i, April 1 and May 1, and two mean starting DO levels, DO_i, 10.35 and 9.30 respectively, to predict the days of nuisance manganese concentrations in 1995. There were 12 weeks of nuisance Mn to begin with, a figure that was reduced by three to four weeks with a 50% reduction in TP and by six to eight weeks with a 75% reduction in TP. Maintaining the reservoir at maximum elevation produced results that were between the 50% and 75% load reductions with a five to seven week reduction of nuisance conditions, and maintaining the maximum elevation combined with a 50% reduction in TP reduced the duration of nuisance conditions by nine to eleven weeks. However, these reductions are maximums for the reasons listed above.

2.18 Colorado Lakes Survey

In 2001, in response to a concern of various city and agency water managers that eutrophication in Front Range drinking water reservoirs was increasing, a Colorado Lakes Survey was developed by Dr. Laurel Saito, Dr. Jim Loftis, and Ms. Marci Koski of Colorado State University. The survey questionnaire contained questions about reservoir physical characteristics, inflow, outflow, and reservoir monitoring, fishery data, uses, issues, cooperative efforts, watershed characteristics, source water characteristics, water quality standards, operating characteristics, seasonal water quality, existing reports and literature, and modeling activities. The management concerns and data gathered by this study formed the basis for this modeling effort.

CHAPTER 3.0 EUTROPHICATION MODELING REVIEW

Eutrophication modeling got its start in the late 1960s with the loading plots of Vollenweider (1968), which were based on Rawson's (1955) insight that deeper lakes are less likely to become eutrophic. These loading plots originally graphed the log of the areal phosphorus loading rates (Lp) vs. log mean depth (H) from northern temperate lakes and divided the graph into three categories (Figure 3.1a): eutrophic lakes with a high loading rate (to left and above line), mesotrophic lakes with a medium loading rate (on line), and oligotrophic lakes with a low loading rate (to right and below line).

Vollenweider (1975) then made the observation that residence time was also a component in the degree of eutrophication of a water body; when comparing impoundments with similar loading rates and depths, those that had a short residence time were less susceptible to eutrophication than reservoirs that had a long residence time. This led Vollenweider to revise his loading plots and use axes of log areal loading rate (Lp) vs. log mean depth/residence time (H/τ_w). The straight line used to define the three trophic groups was now better defined by a curve (Figure 3.1b). The horizontal axis was then noted as being equal to q_s, the hydraulic overflow rate used in sedimentation tank

Figure 3.1a Vollenweider (1968)

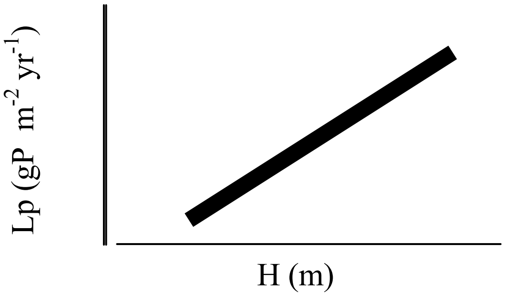
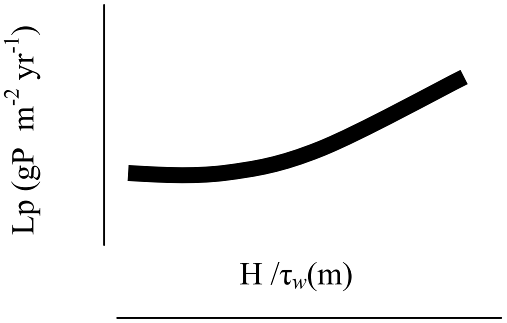


Figure 3.1b Vollenweider (1975)



design by water and wastewater treatment engineers. Vollenweider (1976) and Larsen and Mercier (1976) then made a final revision to the plots by changing the horizontal axis to log $q_s(1 + \tau_w^{1/2})$.

The loading plots, although useful in predicting a lake's trophic status from its loading rate, depth, and residence time, show their limitations when one wants to model the response of a lake to varying phosphorus loads. It was soon realized by Vollenweider (1976) that a phosphorus mass-balance could provide the same predictions of trophic status as loading plots and could also respond to varying loads. A mathematical model is a quantitative representation of such a process using one or more mathematical equations. The advent of mathematical models such as Vollenweider's opened up the study of eutrophication to the increasing complexity of computational models, and the late 1970's saw the development of the first hydrodynamic models of reservoirs. Their predictive abilities make them an appropriate tool to use to reach the goals of this project. To successfully achieve the objectives the model(s) selected should be able to represent:

- Physical processes such as thermal stratification and inflow/outflow
- Physical properties such as Secchi depth
- Chemical processes such as DO depletion, oxidation-reduction
- Biological processes such as chlorophyll-a levels

Models are currently divided along many lines, a few of which are described here to aid in categorization of the models used in the present study.

Empirical vs. Mechanistic models: Empirical models are based on an inductive or data-based approach to assimilative capacity. Often, data from many systems similar to the water body in question are statistically analyzed to estimate the assimilation factor, which is the amount of nutrients that a water body can assimilate in one year. These models have some significant limitations but have proved valuable in lake eutrophication studies (Chapra, 1997). Empirical models are widely used because they are so easy to apply and because they can provide useful order-of-magnitude estimates. However, they also have some very significant shortcomings:

- Heterogeneous populations of impoundments (wide, shallow impoundments vs. long, narrow impoundments) are often used as the basis to develop the regressions for assimilation capacity. The wide variation in impoundments may not satisfactorily reflect the actual conditions at one specific impoundment.
- The use of log-log plots and the wide scatter exhibited by the data creates substantial prediction error, which the untrained user often ignores, creating highly uncertain predictions with unwarranted confidence (Chapra, 1997).
- The lack of a mechanistic basis limits their ability to predict future conditions under certain situations as they assume steady state conditions (see below). It would be very difficult to estimate the effect of modifications to the impoundment, such as increasing or decreasing the volume or loading or adding mechanical aeration.

Mechanistic models, on the other hand, are based on a deductive or theoretical approach using the governing physical, chemical, and biological laws of nature: the conservation of mass, advection and diffusion of matter, and biogeochemical cycling of chemicals among others. Mechanistic water quality water models apply the conservation of mass to a finite volume of water predicting transfers across system boundaries and transformations within the boundaries. These equations for transfer and transformation typically include calibration terms to account for differing conditions between reservoirs. Mechanistic models, however, also have drawbacks:

- When compared to empirical models, mechanistic models are more computationally intensive. In order to appropriately model some transformations or transfers, computational volumes may become so small that calculations can't be economically or physically carried out.
- Mechanistic models may include conceptual errors or may not include all important process, leading to erroneous results.
- User training for mechanistic models is often a significant requirement because a basic understanding of the model's operating principles is necessary and calibration can be an onerous process.

Steady-state vs. Dynamic models: Steady-state models assume that all parameters influencing the model do not change within a modeling period. This makes the implementation of a steady-state model much simpler than a dynamic model. Dynamic models, by definition, have parameters that change with time. Steady-state models are useful to predict the state that a reservoir will reach after a period of adjustment whereas dynamic models are useful when one wants to investigate what happens during the time while equilibrium is being reached.

- Steady-state models have major drawbacks when the operating conditions change significantly over time.
- Dynamic models require additional development and implementation work to incorporate changing inputs and outputs.

Zero vs. One, Two and Three-dimensional: Models can be further classified according to their spatial dimensions, and hence, computational complexity. Time is not considered a dimension in this category as it has already been covered in the steady-state vs. dynamic model discussion. Zero-dimensional models simulate an impoundment as one single cell with no changes in constituents throughout the reservoir. One-dimensional models simulate an impoundment with changes in properties occurring over one dimension, usually in the vertical dimension to create layers. Extending the concept, two-dimensional models and three-dimensional models simulate impoundments with changes in properties occurring over two dimensions and three dimensions, respectively. Dimensional complexity has the following advantages and disadvantages:

- Models with less dimensional (zero or one dimensional) complexity are less computationally intensive.
- Models with more dimensional complexity (two or three dimensional) are more computationally intensive.
- Additional dimensional complexity does not always yield greater model accuracy or precision.

3.1 Current Eutrophication Modeling Possibilities

After reviewing the literature there were found to be a number of models that have been applied to the problem of eutrophication. They are presented in order of ease of implementation, which was defined as the estimated amount of time necessary to take the model from literature review to implementation of a fully functional model. The ease of implementation was defined as follows:

Simple – <1 person-month required to implement (Table 3.1)

Medium – 1 person-month to 1 person-year to implement (Table 3.2)

Complex – >1 person-year to implement (Table 3.3)

Table 3.1 Simple Ease of Implementation Models

	Model		
	Horne	Molot	Vollenweider
Reference	Horne, 1993	Molot, 1992	Vollenweider, 1976
Ease of Implementation	simple	simple	simple
Empirical or Mechanistic	empirical	empirical	mechanistic
Steady State or Dynamic	steady state	steady state	dynamic
Assumptions	fully mixed hypolimnion, linear DO demand, Standley Lake conditions	Ontario lake conditions	fully mixed hypolimnion, linear DO demand
Dimensions	0	1	0
Input	Hypolimnion DO and inflow data over one year	Bathymetry, TP and DO at spring overturn	Simple bathymetry, inflow and outflow data, lake TP concentrations
Output	Hypo DO, TP, NO3, Chl a	Vertical profile of DO at end of season	Hypo DO, TP
Notes	Has not been validated	Extremely easy setup, Questionable application to CO reservoirs	Original mass-balance model of phosphorus, Modified to include DO simulation

Table 3.2 Medium Ease of Implementation Models			
	Model		
	BATHTUB	EUTROMOD	Chapra and Canale
Reference	Walker, 1986	Reckhow, 1990	Chapra and Canale, 1988
Ease of Implementation	medium	medium	medium
Empirical or Mechanistic	mechanistic	mechanistic	mechanistic
Steady State or Dynamic	steady state	steady state	dynamic
Assumptions	fully mixed hypolimnion	fully mixed	fully mixed hypolimnion, linear DO demand
Dimensions	0	0	0
Input	Bathymetry, I/O properties	Watershed composition, Bathymetry, I/O properties	Simple bathymetry, inflow and outflow data, lake TP concentrations
Output	TP, Chl a, Secchi depth	TP, TN, Chl a, Secchi depth, Prob. Anoxia, BG Algae	Hypo DO, TP
Notes	Uses variety of models to obtain predictions	Uses USLE to compute watershed loading	Modified Vollenweider model that incorporates sediment release of phosphorus during anoxic periods

Table 3.3 Complex Ease of Implementation Models				
	Model			
	MINLAKE	DYRESM Water Quality	CE-QUAL-W2 Ver. 2	CE-QUAL-W2 Ver. 3
Reference	Riley and Stefan, 1988	Hamilton and Schladow, 1997	Cole and Buchak, 1995	Cole and Wells, 2000
Ease of Implementation	complex	complex	complex	complex
Empirical or Mechanistic	mechanistic	mechanistic	mechanistic	mechanistic
Steady State or Dynamic	dynamic	dynamic	dynamic	dynamic
Assumptions	fully mixed by layer	fully mixed by layer	mixed layers, simplistic SOD & aquatic microbes	mixed layers
Dimensions	1	1	2	2
Input	Bathymetry, Meteorology, I/O properties, Initial Profile	Bathymetry, Meteorology, I/O properties, Initial Profile	Bathymetry, Meteorology, I/O properties, Initial Profile	Bathymetry, Meteorology, I/O properties, Initial Profile
Output	Vertical profile of modeled constituents	Vertical profile of modeled constituents	Vertical profile of modeled constituents	Vertical profile of modeled constituents
Notes	Could not find code	Many input files required, Replaced by DYRESM CAEDYM	Challenging setup, Results worth effort?	Challenging setup, Results worth effort?

The models detailed in Table 3.1 through Table 3.3 were then judged based on the following criteria that relate to their ability to predict eutrophication problems:

- Ability to predict anoxic conditions
- Ability to predict TP over multiple years

The ability to predict anoxic conditions was determined to be a necessity due to the fact that anoxic conditions are necessary for the reduction of Mn and Fe to the water-soluble forms that create treatment problems. Predictive ability over multiple years was required because the use of a model as a management tool necessitates the ability to predict what conditions are going to be like in five years from a change that occurs today. The ability to predict chlorophyll-a concentrations and Secchi depth, although important, were not considered because many correlations have been developed to predict these values based on TP concentrations.

These criteria eliminate the BATHTUB model because of its inability to predict anoxic conditions and the Horne and Molot models because of their inability to predict dissolved oxygen conditions over a period greater than one season. EUTROMOD, although it gives a probability of whether anoxic conditions occur, is also eliminated because it is not able to provide any information on how severe the anoxia is or its duration. This leaves the Vollenweider and the Chapra and Canale models for further evaluation.

When considering the models in Table 3.3, those considered complex in the ease of implementation category, an additional factor was used to select the models because all models have the ability to predict the required DO and TP values. Due to time constraints, only models that had been previously implemented were considered for further evaluation, thus selecting the CE-QUAL-W2 model of Aurora Reservoir.

3.2 Selected Model Review

3.21 Vollenweider Model

The Vollenweider model was detailed in the first section of this chapter as one of the first models to be developed for analysis of eutrophication problems. The Vollenweider model is a mechanistic, dynamic, one-dimensional model of the whole lake. It requires data on morphometry, total phosphorus loading rates, outflow rates and total phosphorus concentrations, and the net phosphorus settling velocity. Net phosphorus settling velocity is the rate at which phosphorus settles minus the rate at which it is resuspended from bottom disturbance.

Vollenweider (1976) wrote one of the first phosphorus mass-balance models as:

$$V\frac{dp}{dt} = W - Qp - k_s Vp \tag{3.1}$$

Where

V = Volume (m^3)

p = Total Phosphorus concentration (mg m^{-3})

t = time (yr)

W = Total Phosphorus loading rate (mg yr^{-1})

Q = Outflow (m^3 yr^{-1})

k_s = Net phosphorus settling rate (yr^{-1})

3.22 Chapra and Canale Model

Chapra and Canale (1991) developed a model to respond to problems that were encountered with the Vollenweider model when non-oligotrophic impoundments were modeled. One important thing to notice in the Vollenweider model is that the sedimentation term is characterized as a one-way loss, which is a reasonable assumption with deep oligotrophic lakes but not for more shallow, eutrophic lakes in which the release of sediment phosphorus can exert an appreciable impact on the lake phosphorus concentration. This category of shallow, eutrophic or mesotrophic lakes includes some of the reservoirs in this study, and the Vollenweider approach starts to show its limitations when phosphorus loads on an impoundment are decreased from historic levels at which the model was calibrated. Chapra and Canale's model improves upon Vollenweider's approach by including the sediment phosphorus in the lake's total phosphorus budget and using a hypolimnetic dissolved oxygen model to predict when phosphorus will be recycled from the sediments to the lake. The sediment-water model for total phosphorus can be written as:

$$V_1 \frac{dp_1}{dt} = W - Qp_1 - v_s A_2 p_1 + v_r A_2 p_2 \tag{3.2}$$

$$V_2 \frac{dp_2}{dt} = v_s A_2 p_1 - v_r A_2 p_2 - v_b A_2 p_2 \tag{3.3}$$

Where

V_1= water volume of impoundment (m^3)

V_2= volume of enriched sediment (m^3)

W = TP load (µg)

v_s = settling velocity of phosphorus from the water to the sediments (m yr^{-1})

A_2 = surface area of the deposition zone (m^2)

v_r = recycle mass-transfer coefficient from the enriched sediments to the water, activated when hypolimnetic DO goes below a trigger point set by user (m yr^{-1})

v_b = burial mass-transfer coefficient from the enriched surface layer to the deep sediments (m yr^{-1})

Q = annual outflow (m^3)

p_1 = whole-reservoir TP concentration (ug/m^3)

p_2 = enriched sediment TP concentration (ug/m^3)

A zero-order (constant-rate) model is then employed to simulate hypolimnetic oxygen during periods when the lake is stratified.

$$DO_h = DO_i - \frac{AHOD}{z_h}(t - t_s) \tag{3.4}$$

Where

DO_h = hypolimnetic dissolved oxygen level (g m^{-3})

DO_i = initial oxygen concentration at the onset of stratification (g m^{-3})

$AHOD$ = Areal Hypolimnetic Oxygen Demand (g m^{-2} d^{-1}), a measurement of oxygen depletion in the hypolimnion during stratification

z_h = average hypolimnion thickness (m)

t = time (d)

t_s = time of onset of stratification (d)

Summer AHOD is then predicted through the following regression equation:

$$AHOD = 0.086p_1^{0.478} \tag{3.5}$$

For dimictic lakes (strongly stratified in the summer and winter), AHOD is predicted in the winter season on the basis of temperature using:

$$AHOD_w = AHOD_s \times 1.08^{(Tw-Ts)} \tag{3.6}$$

Where

T_s = temperature at which summer $AHOD_s$ is measured and the

T_w = temperature (°C) corresponding to the desired winter AHOD_w.

The model, which is mechanistic, dynamic, and zero-dimensional, has been calibrated and validated on Shagawa Lake, Minnesota (Chapra and Canale, 1991). Its requirements are somewhat greater than Vollenweider's, requiring information on phosphorus recycle and burial rates and greater morphometry data in addition to total phosphorus loading rates, outflow rates, total phosphorus concentrations, and net phosphorus settling velocity.

3.23 CE-QUAL-W2

CE-QUAL-W2, a two-dimensional, dynamic, mechanistic model, had its first predecessor appear as LARM (Laterally Averaged Reservoir Model), published in a report to the United States Army Corps of Engineers (Edinger and Buchak, 1975). Originally designed for a reservoir with no branches, the model was revised to handle multiple branches and estuarine boundary conditions and renamed GLVHT (Generalized Longitudinal-Vertical Hydrodynamic Transport Model). Water quality algorithms were added to the GLVHT code by the Water Quality Modeling Group at the US Army Engineers Waterway Experiment Station and resulted in Version 1.0 of CE-QUAL-W2. Numerous revisions to the model code to improve computational efficiency and accuracy plus add model versatility were incorporated for Version 2.0. CE-QUAL-W2 is a two dimensional hydrodynamic and water quality model that has the ability to model up to 21 different constituents in addition to temperature. The current revision, Version 3.0, again increased computation efficiency and added the ability to model entire waterbasins including multiple reservoirs and the joining river sections. The algorithms defining CE-

QUAL-W2 will not be defined here, but can be found in Cole and Buchak, 1995 (Version 2.0) and Cole and Wells, 2000 (Version 3.0).

CHAPTER 4.0 MODELING DISCUSSION AND RESULTS

For reasons detailed in the preceding chapters, the Chapra and Canale and the Vollenweider models were tested on Aurora and Horsetooth Reservoirs and Standley Lake. In addition, the CE-QUAL-W2 Version 2.0 model developed by Hydrosphere was run on Aurora Reservoir. The start time of each model varies due to monitoring data available for each reservoir, with Aurora Reservoir and Standley Lake starting in 1997 and Horsetooth Reservoir in 1999. All reservoir simulations were ended at the end of 2003, two years after the latest monitoring data.

4.1 Actual Reservoir Conditions

For comparison with model results, the actual observed whole-reservoir TP and hypolimnion DO conditions are detailed in Figures 4.1, 4.2, and 4.3. The values for Aurora were obtained at the Inlet Tower with TP measurements representing an average of surface and 1 meter from the bottom values and hypolimnion DO representing an average of measurements at 40, 50, 60, 70, and sometimes 80 feet. Horsetooth Reservoir measurements were taken by boat in Soldier Canyon section of the reservoir. Different protocols were used, with 1997- April 1999 data representing composite surface, epilimnion, and hypolimnion samples. May 1999 – August 2000 data represent the average of TP data obtained at 5-meter depth intervals and hypolimnion DO data representing the average of data obtained at 5-meter depth intervals starting at 15 meters. A near-central monitoring point was used for Standley Lake with TP values representing an average of 1.0 and 21.0 meter depths. Hypolimnion DO values represent an average of all DO readings taken at greater than 12 meters (approximately 1-2 meter depth interval). They all show a general trend of a well-oxygenated hypolimnion during the winter with an oxygen deficit developing during the late summer as the reservoirs become increasingly stratified. This period of anoxia corresponds with an increase in TP levels and manganese problems in some reservoirs. After fall turnover, the reservoirs again become well-oxygenated and the TP levels and manganese problems decrease once more.

Figure 4.1: Aurora Reservoir TP & Hypolimnion DO

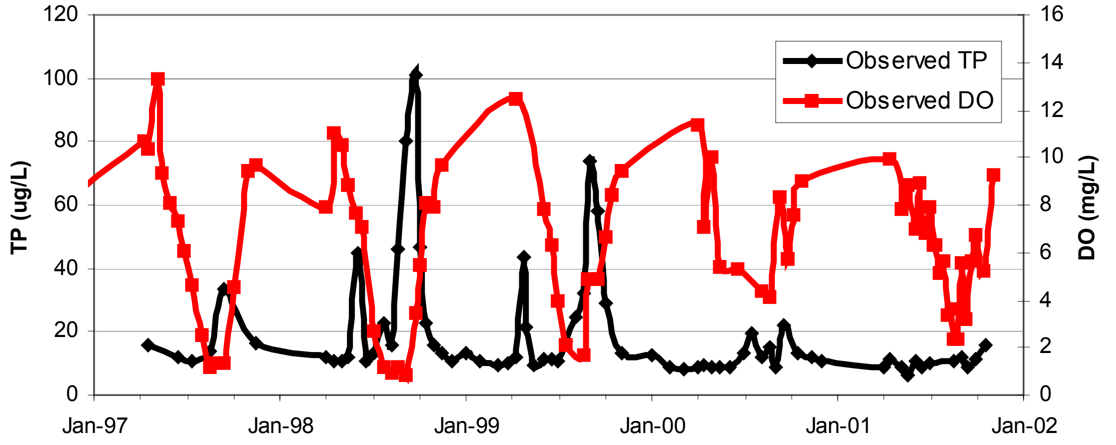
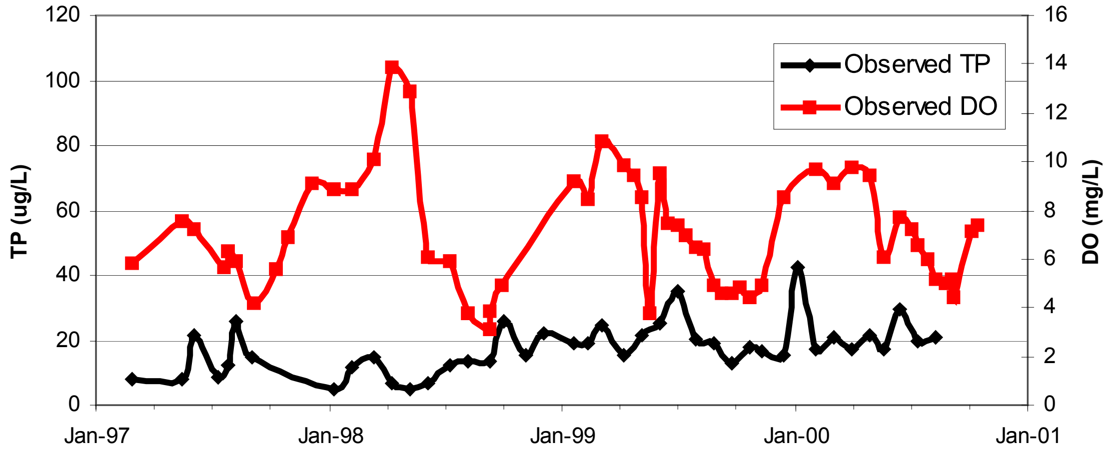


Figure 4.2: Horsetooth TP & Hypolimnion DO



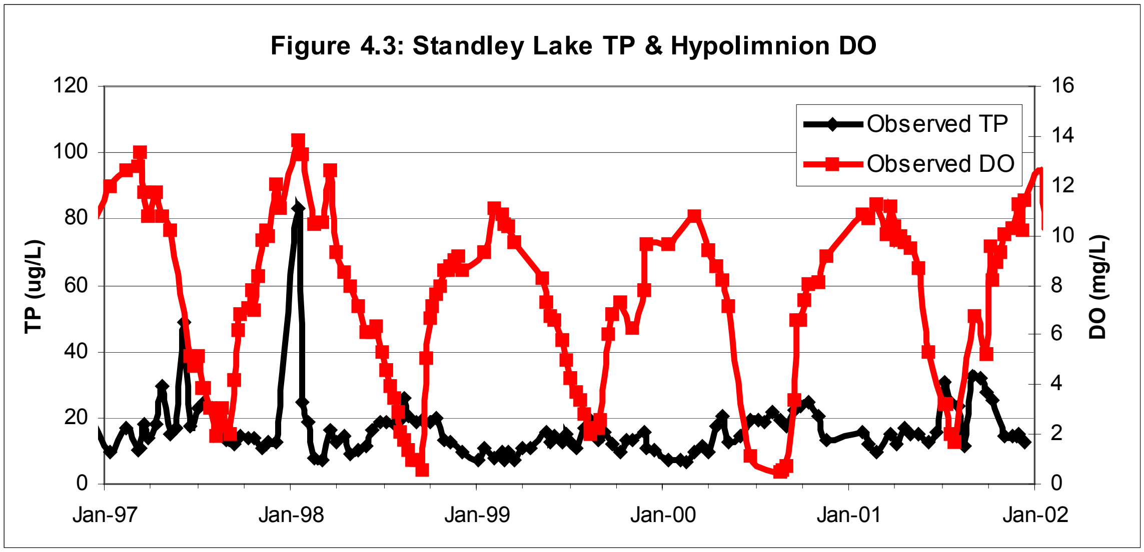


Figure 4.3: Standley Lake TP & Hypolimnion DO

The extended period of monitoring data available for Aurora Reservoir and Standley Lake lends itself to division into calibration and validation periods for model development. The calibration and validation periods used are shown in Table 4.1. The absence of a validation period for Horsetooth is explained in the following paragraphs.

Table 4.1 Calibration and Validation Periods

Reservoir	Calibration Period Start	Calibration Period End	Validation Period Start	Validation Period End
Aurora	4/22/1997	4/13/1999	4/27/1999	10/23/2001
Horsetooth	5/10/1999	8/14/2000	-	-
Standley	1/16/1997	12/7/1998	1/7/1999	12/17/2001

With Horsetooth Reservoir, there appears to be a dichotomy between the first two years of reservoir monitoring data and the second two years, as the TP data after May 1999 is generally near 20 µg/L and the data before May 1999 are often below 20 µg/L. This could be explained by the change in monitoring techniques from surface, epilimnion, and hypolimnion composite sampling in 1997-98 to 5-m interval sampling in

May 1999-2000. Due to this fact, the data from 1997 to April 1999 will not be used in calibration of the Horsetooth models. It is due to this fact that modeling of Horsetooth Reservoir began in 1999. This also means that only TP data from May 1999-2000 will be used for calibration, and the validation period of Horsetooth Reservoir will be eliminated because the remaining data set is less than two years long. DO data for comparison with model prediction is collected separately from TP data, so DO comparison begins in January 1999.

Another problem arises with Horsetooth Reservoir in that it is physically the most complex of the three reservoirs, consisting of three distinct basins plus one disconnected bay. Due to input data limitations, this reservoir was modeled as one fully mixed system, with readings at Soldier Canyon being considered representative of the whole.

4.2 Development of Inputs

Although the models chosen for implementation are fairly straightforward, they contain equations, and hence require some inputs to be calculated. Model inputs that must be developed included morphometric parameters; such as surface area, average depth, and average volume, and load parameters; such as outflow, TP inflow, and TP outflow.

To calculate morphometric parameters, data on the maximum and minimum volume of each reservoir was obtained for the years from 1995-2000 from the Colorado Lakes Survey. These yearly maximum and minimum data were averaged to determine the mean volume for each year. The mean volume for each year from 1995 to 2000 was then averaged and used as the mean volume of the reservoir for the period from 2001 to 2003 (Table 4.5). This assumption does not take into account the current drawdown of

Horsetooth Reservoir for construction activities or the current effect of reduced water supplies in decreasing water levels at Aurora Reservoir and Standley Lake. The mean volume for each reservoir from 1995-2000 was used with the corresponding Elevation vs. Surface Area/Volume chart to estimate the mean surface area for the entire modeling period. The mean volume for the 1995-2000 period was then divided by the mean surface area to obtain the mean reservoir depth. These mean parameters are shown in Table 4.2.

Table 4.2 Mean Reservoir Parameters from 1995-2000

Reservoir	**Surface Area, A or A_1 (ha)**	**Volume, V or V_1 (m^3)**	**Mean Depth, z (m)**
Aurora	312	3.61E+07	11.6
Horsetooth	719	1.43E+08	19.8
Standley	464	4.71E+07	10.2

To determine the reservoir stratification and overturn dates and related data such as average depth to the hypolimnion and hypolimnion thickness, reservoir temperature and DO profiles were examined. The limited temporal and spatial resolution of the data required interpolation of the average date of stratification and stratification decay. Analyzing profile data for all three reservoirs over several years from 1995-2000 revealed that all showed a strong stratification beginning in early to mid-May (Table 4.3). This date is about 20 days earlier than that used by Chapra and Canale in their model, which can be explained by the fact that Colorado is situated farther south than Minnesota, so the reservoir water warms earlier and cools later. The stratification then begins to break down in early to mid October, which is about 20 days later than that used by Chapra and Canale in their model. Both dates also correspond well with those estimated by the reservoir operators in the Colorado Lakes Survey. DO data at the spring stratification date were averaged to estimate the mean DO at the beginning of stratification (Table 4.4).

Table 4.3. Reservoir Stratification

Average Start Date	Julian Day	Calendar Date
Spring Turnover	1	1/1
Spring Stratification	130	5/9
Fall Turnover	285	10/11
Fall Stratfication	365	12/31

Table 4.4 Reservoir Hypolimnion Parameters

Reservoir	Depth to Hypolimnion (m)	Mean Starting DO, DO_i (mg/L)	Mean Temp C	Surface Area of Deposition Zone, A_2 (m^2)	Mean Volume (m^3)	Mean Thickness, z_h (m)
Aurora	12	9.55	14	1.39E+06	9.45E+06	6.8
Horsetooth	12	9.61	12	5.13E+06	7.50E+07	14.6
Standley	12	9.10	16	1.47E+06	8.40E+06	5.7

Once the average starting and ending dates for stratification were determined, a day about 3/5ths of the way between the two dates was located in the dataset, approximately early-to-mid August, and the depth to the hypolimnion (point where thermocline ends) and the mean hypolimnion temperature at this date were determined. The reason 3/5ths was selected is it roughly corresponds to the date when the DO in the hypolimnion of Aurora Reservoir and Standley Lake start to go below 5 mg/L, which is the level at which Jassby and Goldman (1996) saw problems develop in Horsetooth Reservoir. It also provides a good idea of the depth of the hypolimnion when anoxia problems begin to occur. An accurate representation of this depth is necessary because after stratification, DO for aerobic decomposition is available only from the hypolimnion. The mean depth to the hypolimnion and the mean reservoir elevation was determined for each reservoir and were then used with the Elevation vs. Surface Area/Volume charts to make an estimate of hypolimnion volume and surface area, which is the same as the surface area of the deposition zone. The average thickness of the hypolimnion was then calculated by dividing hypolimnion volume by area. We should note that the definition of 5mg/L as a threshold for “low” DO concentrations is somewhat arbitrary. A level of 2mg/L is often used as a threshold for “anoxic” conditions, and other limits may be appropriate, depending on the circumstances.

Observed mid-August DO profiles for the threes study reservoirs are shown in Figures 4.4 to 4.6. All three reservoirs showed a similar mean depth to the hypolimnion (Figures 4.4, 4.5, and 4.6) of approximately 12 meters for each year. Therefore, in all following sections all references to hypolimnion properties will refer to measurements of 12 meters or below. DO data was used in these plots because they show the property of interest. Temperature profiles closely mirror the DO pattern.

Horsetooth Reservoir’s measured DO plot is interesting in that it shows a ‘rebound’ action in DO as one passes through the middle of the hypolimnion with DO decreasing again as one approaches the bottom sediments. It should also be noted that Horsetooth Reservoir has much greater DO readings in mid-August than Aurora Reservoir and Standley Lake. It is theorized that these findings are due to the greater hypolimnetic volume in Horsetooth or high DO water entering the hypolimnion.

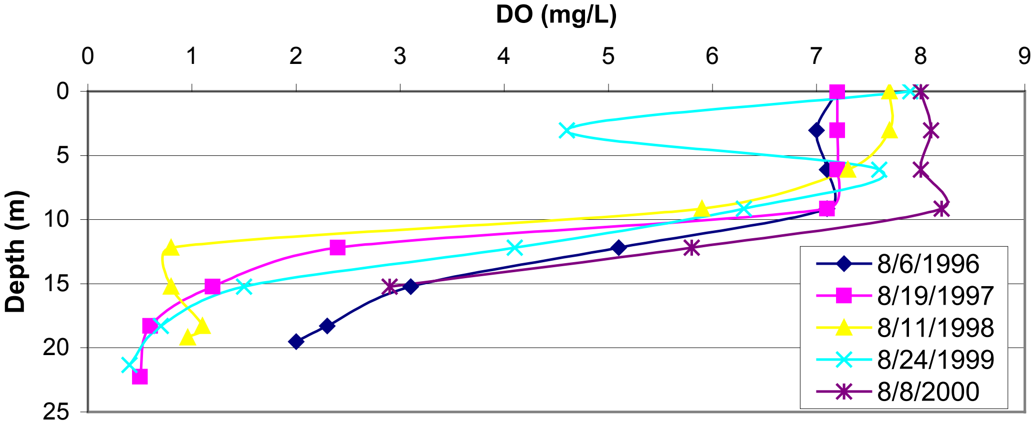


Figure 4.4: Observed Aurora Reservoir mid-August DO Profile

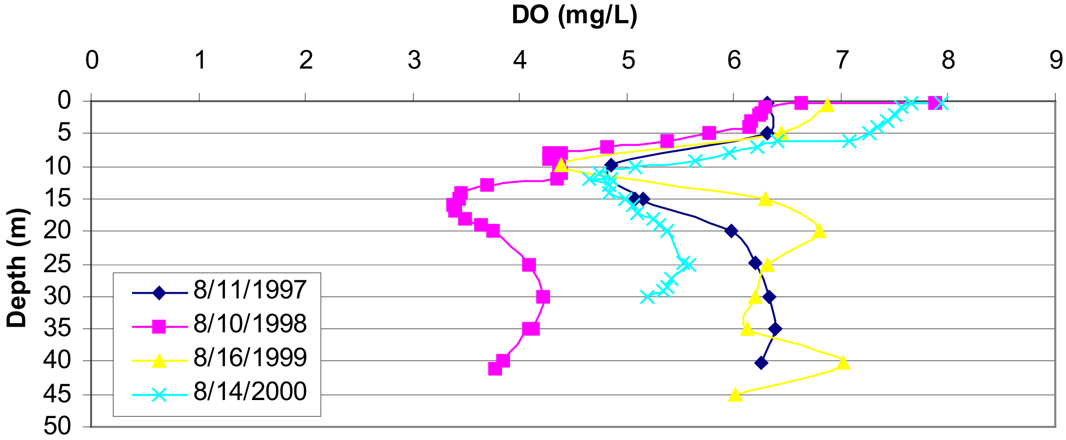


Figure 4.5: Observed Horsetooth mid-August DO Profile

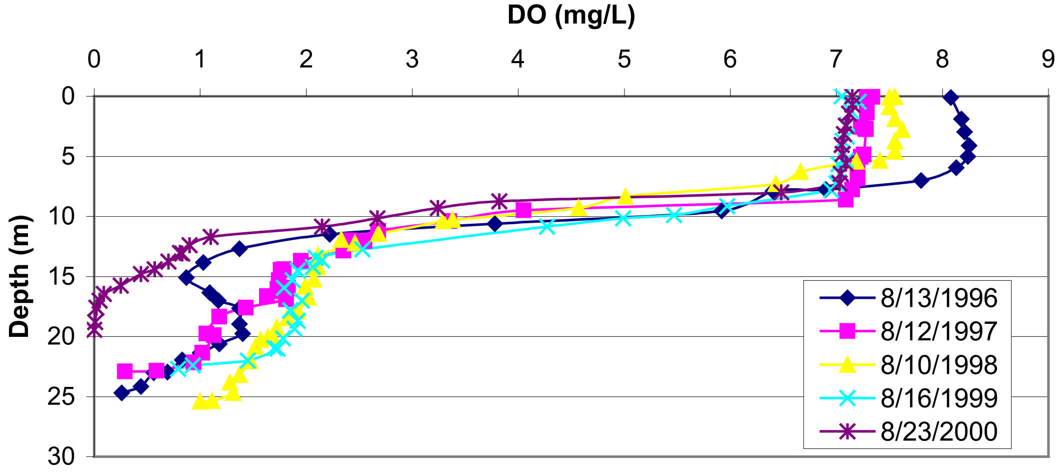
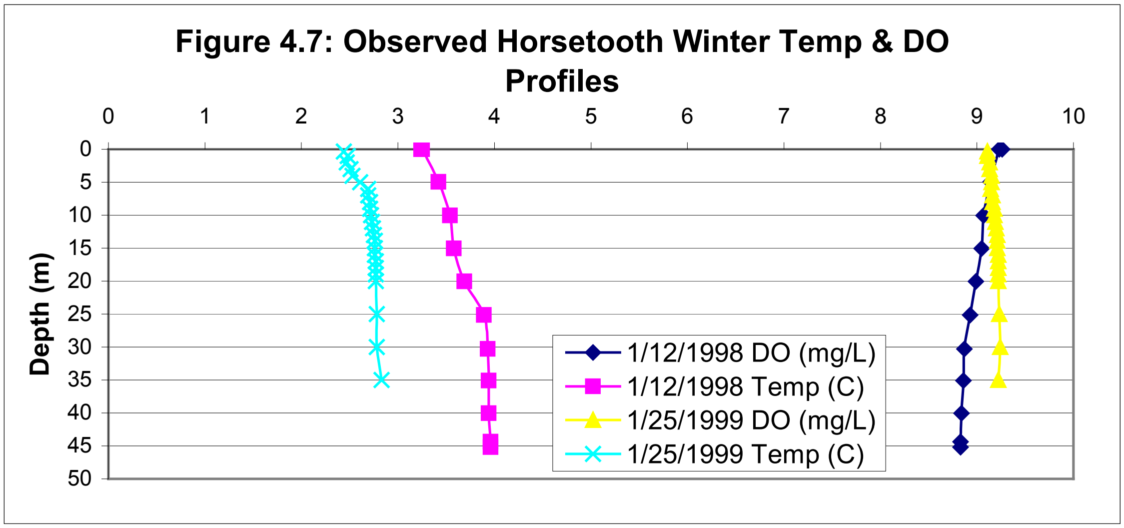


Figure 4.6: Observed Standley Lake mid-August DO Profile

While determining the lake turnover parameters for Standley Lake and Horsetooth Reservoir, it was noticed both reservoirs are monomictic, or mix once per year. Mid-to-late January is the coldest part of the year in the northern hemisphere, so if winter stratification is going to occur, it would show up in mid-to late January temperature profiles (Figures 4.7 and 4.8). This creates some problems with the models that are being used to model the systems, which assume a dimictic lake, or mix twice per year. The models can easily be adapted to a monomictic situation by changing the turnover dates of the reservoir to stratify on December 31 and turnover on January 1 (see Table 4.3), but this does create a question when looking at the data for Aurora Reservoir, as the temperature and DO data record is not complete enough at the beginning and end of the year to determine if the lake is mono or dimictic. Since both Standley and Horsetooth are monomictic and because Aurora reservoir is fairly closely related to Standley Lake in physical parameters such as depth and volume, the assumption was made that Aurora is monomictic for implementation of the models.



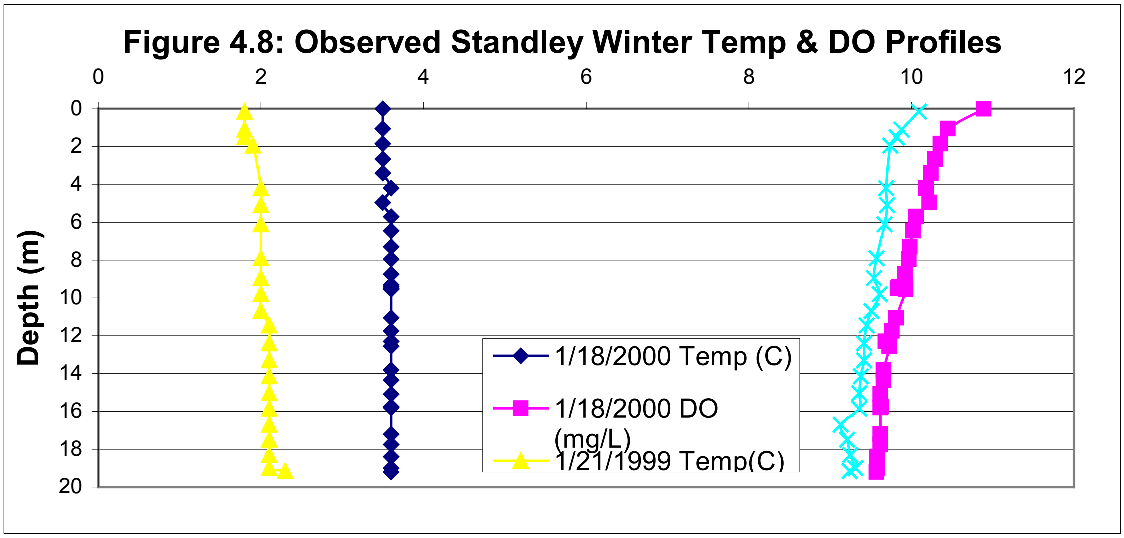


Figure 4.8: Observed Standley Winter Temp & DO Profiles

For all three study reservoirs, TP inflow load was estimated by summing the following sources: gauged runoff (imported from another watershed), ungauged runoff (local watershed), atmospheric deposition, and other (loads from waterfowl at Aurora and Standley, loads from septic systems at Horsetooth). Total TP loads for each year are given in Table 4.5 with details of each year's TP components shown in Appendix A. The techniques used to calculate these values are described in the following paragraphs.

Gauged runoff is monitored to varying degrees at each of the three reservoirs. All reservoirs collect and report total inflow data on a daily or monthly basis. At Aurora Reservoir, data were available on inflow water quality for pipeline and some well water. If enough data points were available, as was the case with the pipeline, yearly estimates were made of the TP concentration. The wells did not have as much data, if they had any at all, so data from all years were averaged to compute an estimate of TP concentration. These estimates were then used to make an estimate of TP concentration for those wells that did not have any data. These average concentrations were multiplied by the corresponding flow data and then summed to give TP loads from gauged runoff.

For Horsetooth Reservoir, data were available for most months on inflow TP through the feeder canal and for those months that did not have data, a yearly average was used. This was multiplied by the monthly canal flow and summed to compute a yearly load from gauged runoff.

At Standley Lake, data were available over the 1997-2000 model period on approximate monthly basis to make an estimate of the TP concentration in the inflow water. This value was multiplied by the flow for the time period that it covered and then summed to compute a yearly load.

To predict TP loading from ungauged runoff, the watershed portion of the EUTROMOD (Reckhow, 1990) spreadsheet developed by Hydrosphere (2000a) for Aurora Reservoir was used at each of the three reservoirs. This requires monthly precipitation data, obtained from the National Climatic Data Center for the nearest weather station (Appendix B) during the period from 1995-2001, along with data on watershed area and land use. This spreadsheet is shown in Appendix C and estimates TP loads to the reservoir by summing two components: dissolved and sediment-attached phosphorus. Dissolved phosphorus was estimated using a version of the rational equation multiplied by concentration values of 70 mg/m^3 for agricultural and residential land and 26 mg/m^3 for parks and open space. These values were obtained from City of Aurora storm water monitoring data and literature values (US EPA, 1999). Sediment-attached TP was estimated by multiplying the long-term average soil loss from the Revised Universal Soil Loss Equation times a sediment delivery ratio of 0.25, enrichment ratio of 2.0, and sediment TP concentration of 660 mg TP/kg sediment. These values were originally used by Hydrosphere (2000b), who estimated the sediment delivery ratio from

Vanoni (1975) and enrichment ratio and sediment TP concentrations from Reckhow (1990).

Atmospheric deposition was estimated for each of the reservoirs using the rate 54.45 kg km^{-2} yr^{-1} determined by Reuter, et al. (2001). This is the same rate used by Black and Veach (2001) at Aurora Reservoir and an updated version of the value used by Jassby and Goldman (1996) at Horsetooth Reservoir. The mean surface area used was that shown in Table 4.2.

Other sources of TP included waterfowl (primarily geese) deposition and septic systems. Black & Veatch (2001) estimated waterfowl deposition at 34 kg/yr for Aurora Reservoir. The Black & Veatch value was used at Aurora Reservoir and was scaled up on the basis of relative surface area to 51 kg/yr at Standley Lake because it serves as a wildlife sanctuary and should have waterfowl population. Jassby and Goldman (1996) did not consider waterfowl a significant source at Horsetooth Reservoir so this study will not, but they did estimate the TP loading from septic systems at 215 kg/yr for Horsetooth Reservoir. Septic systems are not known to be in operation at either Aurora Reservoir or Standley Lake.

Outflow data (Table 4.5) were required by the Vollenweider and the Chapra and Canale models to estimate quantity of phosphorus removed from the reservoir. Aurora Reservoir has one gauged outflow, so total flow measurements were obtained from the inflow/outflow tower. Horsetooth Reservoir has multiple gauged outflows for irrigation, for Horsetooth Reservoir. Septic systems are not known to be in use at Aurora Reservoir City of Fort Collins, and regional water use, so these flows were summed for a total outflow. Standley Lake also has one gauged outflow. An average of the outflow values from 1995-2000 was used for Horsetooth Reservoir and Standley Lake for the period from 2001 to 2003 for which no data were available. At Aurora Reservoir the future outflow was extrapolated to 12 x 10^6 m^3/yr from 1999 and 2000 data because of increasing outflows throughout the survey period as demands on the reservoir increased due to growing population. For each reservoir, the total yearly flow was transformed to a daily average.

Table 4.5 Volume, Outflow, and TP Loads

Aurora Reservoir

Year	Mean Volume (m^3)	Outflow (m^3)	TP Load (kg)
1997	3.71E+07	2.66E+06	533
1998	3.65E+07	4.14E+06	516
1999	3.93E+07	4.22E+06	586
2000	3.29E+07	9.01E+06	583
2001	3.65E+07	1.20E+01	554
2002	3.65E+07	1.20E+01	554
2003	3.65E+07	1.20E+01	554

Horsetooth Reservoir

Year	Mean Volume (m^3)	Outflow (m^3)	TP Load (kg)
1997	1.70E+08	1.05E+08	5374
1998	1.38E+08	1.45E+08	2844
1999	1.43E+08	8.86E+07	4655
2000	7.85E+07	1.76E+08	2912
2001	1.32E+08	1.29E+08	3946
2002	1.32E+08	1.29E+08	3946
2003	1.32E+08	1.29E+08	3946

Standley Lake

Year	Mean Volume (m^3)	Outflow (m^3)	TP Load (kg)
1997	4.93E+07	4.39E+07	2799
1998	4.88E+07	5.61E+07	4674
1999	4.88E+07	4.31E+07	3710
2000	4.53E+07	4.63E+07	1635
2001	4.80E+07	4.74E+07	3204
2002	4.80E+07	4.74E+07	3204
2003	4.80E+07	4.74E+07	3204

TP outflow loads were computed by multiplying TP concentrations and outflow volume. Outflow water quality has been measured at both Aurora Reservoir and Standley Lake, with a much more detailed program in effect at Standley Lake. Based on mean in-lake:outflow ratios at Aurora Reservoir Lake, the outflow TP concentration at Aurora Reservoir was estimated as 93% of the in-lake concentration for the duration of the model simulation. Standley Lake's monitoring data were comprehensive enough to compute the TP outflow for each year from 1997-2000. Due to the variance between reservoirs in outlet number, design, and location, estimates for Aurora Reservoir and Standley Lake are not applicable to Horsetooth Reservoir, so outflow concentration was assumed to be 100% of the in-lake concentration for the duration of the model simulation. This should be revised as more data becomes available.

Both of the simple models were implemented with an assumption of a constant volume during each year. To more properly account for phosphorus at the end of the year when a change in volume occurs, a yearly phosphorus mass balance was implemented. To accomplish this the mean volume for the ending year is multiplied by the TP concentration to give a total TP mass. The TP mass is then divided by the mean volume for the next year to give the TP concentration at the beginning of the year. For most years, this does not create much of a discontinuity, however, this can create an abrupt change in TP concentration at the start of the year. As an example, Horsetooth Reservoir is currently experiencing a period of excessive drawdown due to construction, producing an extremely low mean volume in 2000 as compared to 1999, producing a spike in TP (Figures 4.10, 4.13) when the year changes.

To develop the CE-QUAL-W2 model of Aurora Reservoir, inflows and outflows were accounted for first. Once inflows and outflows are properly accounted for by predicting the correct reservoir volume, temperature predictions are checked because of their importance on biogeochemical cycling rates. After this was completed to a satisfactory level, calibration of individual water quality parameters such as DO and TP could proceed. As noted before, due to the time involved in setting up and calibrating a CE-QUAL-W2 model, a CE-QUAL-W2 model of Aurora Reservoir by Hydrosphere (2000b) was used.

4.3 Development of Initial Parameters and Calibration

To begin the model simulations, estimates were needed of the average lake TP concentration for the year before modeling started (used in AHOD estimation), and of the TP concentration at the beginning of the model. The mean whole-reservoir TP concentration for the previous year was estimated by averaging the TP values for the two-year calibration period (Table 4.1) of the reservoir. TP concentration at the beginning of the model simulation (January 1, 1997 or January 1, 1999) was estimated by using the observed value exactly one year ahead (January 1, 1998 or January 1, 2000) because monitoring data did not exist at the start of the model run. This resulted in the initial parameters contained in Table 4.6.

Table 4.6 Mean and Initial TP Values (mg/m^3)

	Reservoir		
	Aurora	**Horsetooth**	**Standley**
2-year mean whole-reservoir TP	22.3	21.7	18.9
January 1 TP one year after start of model	13.0	29.0	11.5

One additional parameter was needed for the TP mass balance in both models, an estimated phosphorus settling rate, v_s. The limited temporal resolution of most of the monitoring data forced the use 20 m/yr as a first estimate of the phosphorus settling rate of all three reservoirs. This value, however, is well within the ranges reported in the literature (Chapra, 1997). This value was adjusted during calibration of the models.

The Chapra and Canale model also requires some additional parameters, including recycle, v_r, and burial velocities, v_b, of phosphorus in the sediments and phosphorus concentration of those sediments. Initial recycle and burial velocities were taken from Chapra and Canales' model of Shagawa Lake and sediment phosphorus concentrations of 336,000 mg/m^3 were estimated from the USGS cores of Standley Lake taken in 1990. This sediment values was used for both Standley Lake and Horsetooth, which are of similar age (approximately 50 years since Horsetooth construction and 50 years since Standley's major expansion), but the estimate was revised downward to one quarter of 336,000mg/m^3, or 84,000 mg/m^3, for Aurora Reservoir, which has been in operation for twelve years, or approximately one quarter the time of Horsetooth Reservoir and Standley Lake.

For DO modeling, the Chapra and Canale method of estimating DO concentrations (AHOD using a TP regression, see equation 3.5 in section 3.22) was used for both models. To predict the time for which the reservoir was anoxic, an estimate of the hypolimnetic DO concentration at which anoxia occurs was needed. The anoxic DO concentration was set at 5 mg/L, as this is close to the value of 5.2 mg/L that Jassby and Goldman (1996) used in their model to define when manganese levels rose above the MCL. This value may seem high, but it represents an average hypolimnetic DO, concentration so it needs to account for the fact that the hypolimnion is not truly 'well-mixed' as our model assumes but actually goes anoxic in the sediments, overlying water, and less well-mixed bays well before the whole hypolimnion would go anoxic.

To assess model performance, the models were calibrated using the first two years of TP monitoring data by minimizing the Root Mean Square Error (Eqn 4.1).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(predicted - measured)\hat{}2}{n}} \tag{4.1}$$

This value was then minimized using the Solver application in Excel (Microsoft, 1999) which was constrained to use the following values: $1 < v_s < 200$, $0.00076 < v_b < 0.0076$, $0.0031 < v_r < 0.31$. The units of all variables are m/yr. The constraints on the values for v_s was determined from the literature (Chapra 1975, Dillon and Rigler 1975, and Thomann and Mueller 1987) and values for v_r were taken to be within one order of magnitude of those used by Chapra and Canale in their model. The values for v_b were taken to be within one order of magnitude lower than that used by Chapra and Canale because higher values produced unstable sediment phosphorus concentrations that decreased faster than it could be replenished. These model parameters were then used on the remaining monitoring data for validation, and this error was computed in the same method as described above. As indicated before, due to the inconsistency of the Horsetooth data and consequent inability to obtain more than two years of data, the models were not validated for Horsetooth.

4.4 Model Sensitivity Analysis

To help determine the effects that uncertainty in estimating the TP load to the different reservoirs has on the resulting whole-reservoir TP concentrations, a sensitivity analysis was conducted by varying the TP load to the Vollenweider and the Chapra and

Canale models of Aurora Reservoir and Standley Lake by 25% in each direction, resulting in loads of 75% and 125% of those estimated using inflow data. A sensitivity analysis was not performed on the CE-QUAL-W2 model because it is not possible to increase only the phosphorus loading to the reservoir as the model takes phosphorus in other partitions (i.e. detritus, DOM, POM) into account when figuring TP concentrations.

The results of these analyses (Table 4.7) show the difference in load/volume ratio between Aurora and Standley. Aurora's volume is about 75% of Standley's but its loads are about 25% of Standley's (Table 4.4). Accordingly, an increase of 25% in Aurora's loading, about 125 kg/yr, causes a smaller change in TP than a 25% increase in Standley's loading, or about 450 kg/yr. Differences in model sensitivity and calibration values also show up, as Aurora's Vollenweider model predicts much larger changes in TP with a change in load than does the Chapra and Canale model. This is partly due to the fact that the calibrated Chapra and Canale model has a phosphorus settling velocity of 164 m/yr whereas the calibrated Vollenweider model has a phosphorus settling velocity of 13 m/yr, greatly increasing the rate at which TP is lost from the system. This is likely due to the fact that phosphorus settling velocity in the Vollenweider model is a net velocity as compared to the Chapra and Canale model in which it is a gross velocity, due to the latter model's inclusion of a recycle term which buffers changes in TP loading.

Table 4.7 Sensitivity Analysis on Mean Whole-Reservoir TP (ug/L) for Model Period				
Aurora Reservoir Models				
	Vollenweider		**Chapra and Canale**	
Loading	**Mean TP**	**%**	**Mean TP**	**%**
75%	16.0	65.7%	11.7	102.2%
100%	24.4	100.0%	11.5	100.0%
125%	24.6	100.8%	14.4	125.3%
Standley Lake Models				
	Vollenweider		**Chapra and Canale**	
Loading	**Mean TP**	**%**	**Mean TP**	**%**
75%	9.6	60.0%	9.4	60.1%
100%	16.0	100.0%	15.7	100.0%
125%	14.8	92.2%	14.4	91.9%

4.5 Vollenweider Model Results

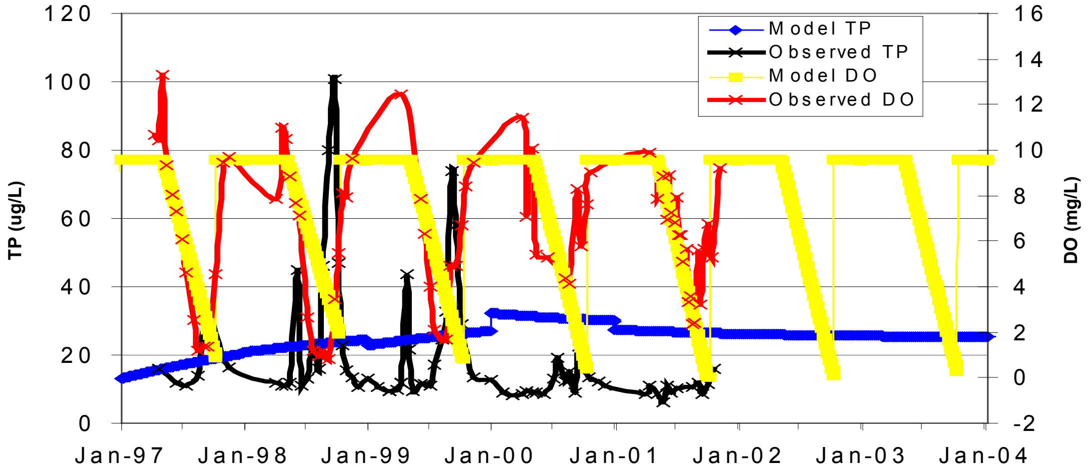


Figure 4.9: Vollenweider Model of Aurora

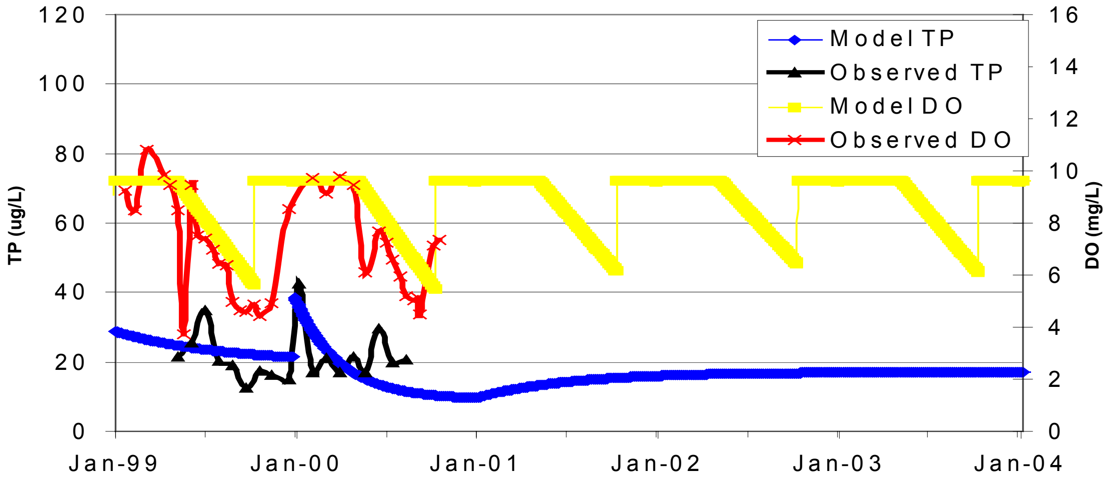


Figure 4.10: Vollenweider Model of Horsetooth

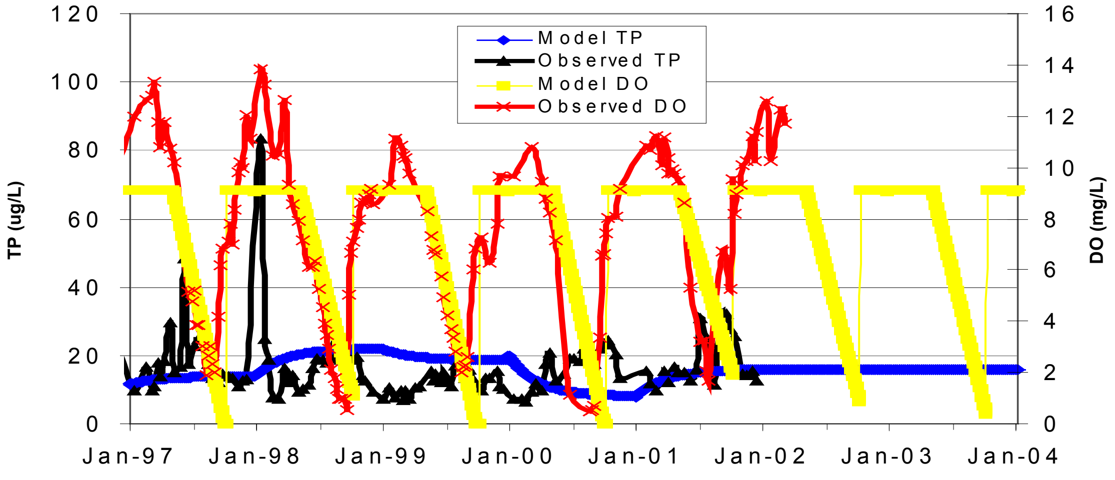


Figure 4.11 Vollenweider Model of Standley

When calibrating the Vollenweider model, the only parameter for adjustment is the net phosphorus settling velocity, v_s. Changes in this value slowly adjusts the whole-reservoir TP value up or down with a respective decrease or increase in v_s. This change impacts DO by changing the mean yearly TP concentration, indirectly increasing or decreasing the amount of organic matter available for decomposition. The optimum calibration values for each model, as determined by RMSE minimization, are shown in Table 4.8. The values were well within the range of those reported in the literature.

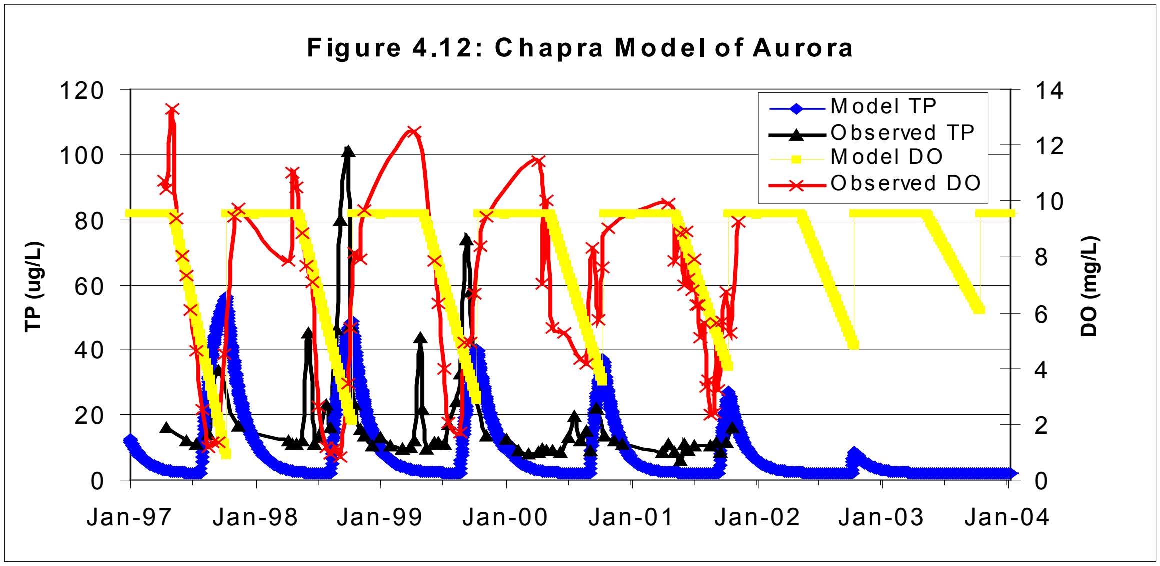
Table 4.8 Vollenweider Calibration

Reservoir	**Net Phosphorus Settling Rate, vs**	**Units**
Aurora	9.18	m/yr
Horsetooth	30.41	m/yr
Standley	109.06	m/yr

Using these calibration values, the Vollenweider models of Aurora Reservoir (Figure 4.9) and Standley Lake (Figure 4.11) cannot predict the intense peaks in reservoir TP concentrations seen in the fall of each year. Changes in phosphorus loading are not enough to recreate these changes. The DO simulation of Aurora Reservoir appears a good approximation as turnover and stratification appear to begin at the appropriate times. Hypolimnion oxygen demand appears to be appropriate for the first two summers (1997 and 1998) and then it appears to overestimate demand for the next three summers. Standley Lake DO simulations appear to have the opposite problem, as HOD (Hypolimnetic Oxygen Demand, the rate at which DO is consumed in the hypolimnion) appears overestimated for the first three summers, predicting zero or near-zero DO when it didn’t occur, and then it closely approximated the demand for the final four summers. Overturn and stratification periods also appear to be correctly estimated.

During the two year calibration period, the Vollenweider model of Horsetooth Reservoir appears to do better job of matching TP in the reservoir than the Vollenweider model of either Standley or Aurora. This is likely due to the fact that DO levels in Horsetooth did not decrease as much in the late summer as in Standley and Aurora, decreasing the amount of TP released by the sediments. The HOD regression appears to seriously overestimate the DO decreases that develop in Horsetooth as readings below 2 are predicted, but actual measurements do not go below 4 mg/L. The general stratification date estimate appears to be correct for Horsetooth Reservoir. It is not possible to make a determination on the general turnover date, as turnover appears to be predicted too early in 1999, but could be correct for 2000. A dataset larger than two years is needed to determine if these general dates were correct estimates for Horsetooth Reservoir. As mentioned earlier, there was no validation period for Horsetooth Reservoir.

4.6 Chapra and Canale Model Results



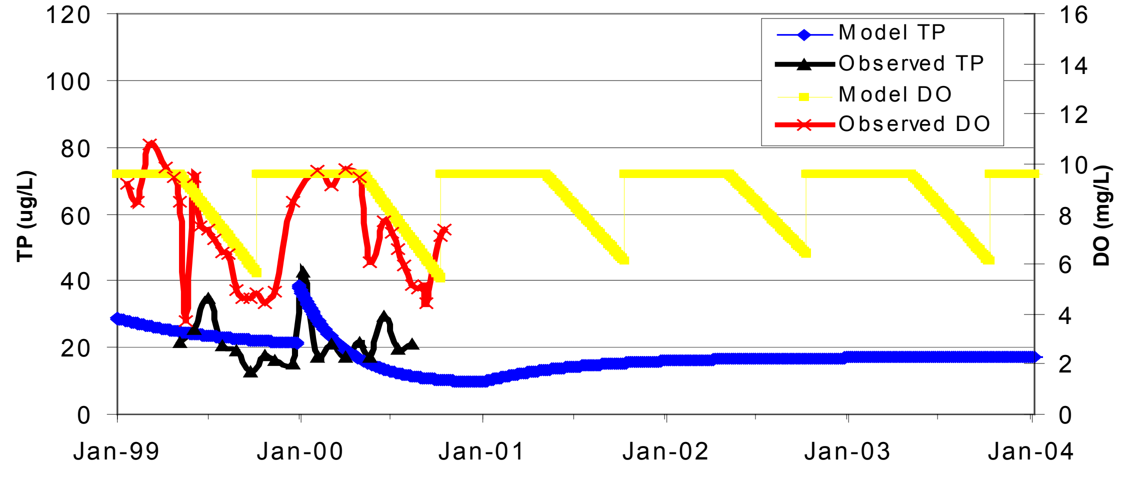


Figure 4.13: Chapra Model of Horsetooth

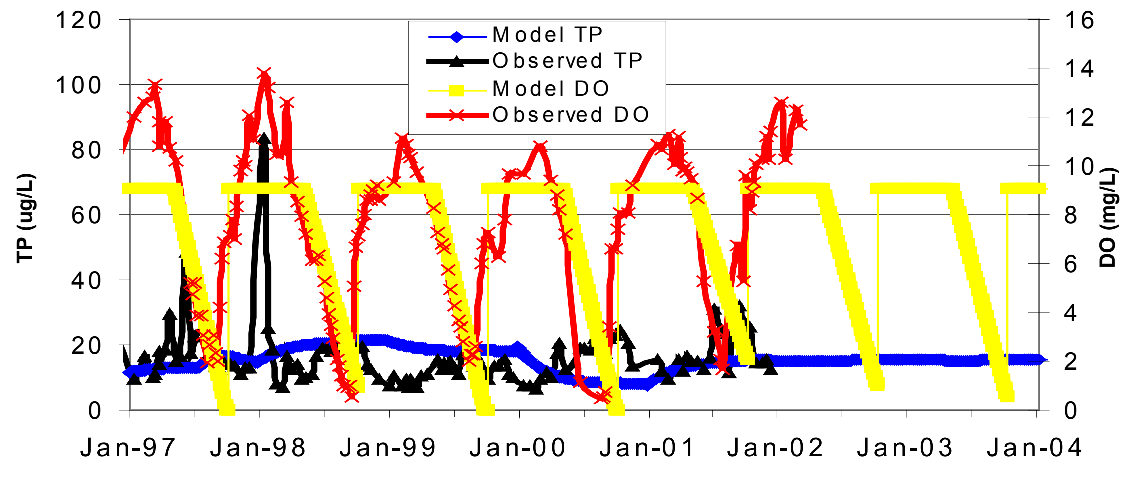


Figure 4.14 Chapra Model of Standley

When calibrating the Chapra and Canale model, as with the Vollenweider model, changing the phosphorus settling velocity helps adjust the whole-reservoir TP concentration. There are also two additional calibration parameters, the recycle and burial velocities, which adjust the amplitude and speed of the phosphorus concentration increases after anoxia occurs and concentration decreases after anoxia dissipates. All of these changes affect DO by changing the whole-reservoir TP concentration, which indirectly increases or decrease the amount of organic matter available for decomposition. The resulting calibration is shown in Table 4.9. As with the Vollenweider model, validation of the model was limited by the short period for which the necessary data were available.

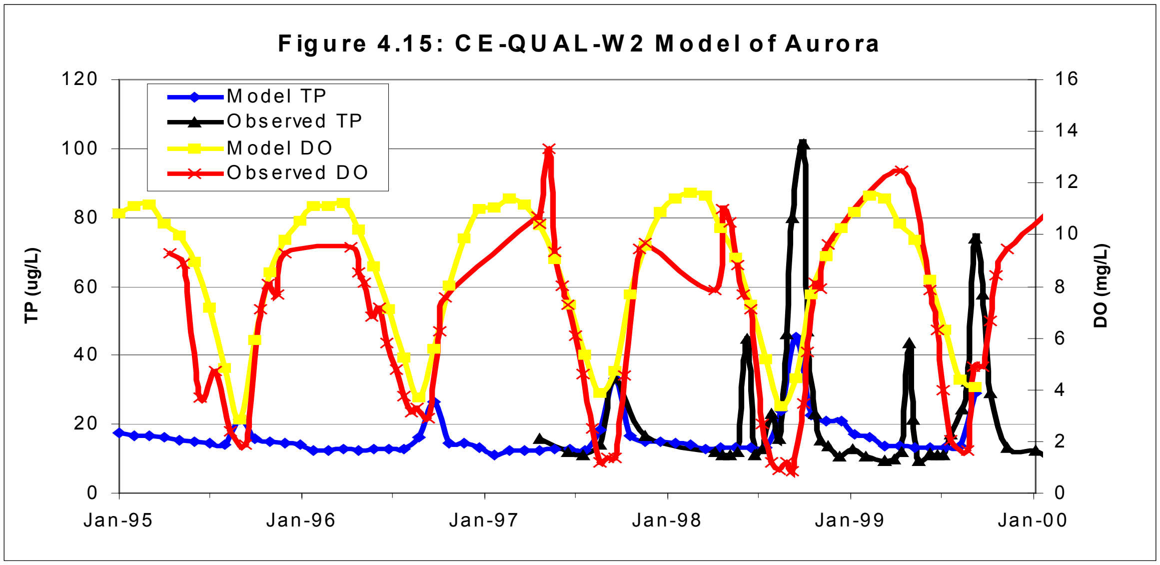
Table 4.9 Chapra and Canale Calibration						
Reservoir	**Net Phosphorus Settling Rate, vs**	**Units**	**Burial Rate, vb**	**Units**	**Recycle Rate, vr**	**Units**
Aurora	200.49	m/yr	0.01276	m/yr	0.3094	m/yr
Horsetooth	30.41	m/yr	0.00077	m/yr	0.0031	m/yr
Standley	115.51	m/yr	0.31722	m/yr	0.0237	m/yr

Unlike the Vollenweider model, the Chapra and Canale model of Aurora Reservoir (Figure 4.12) did a much better job of predicting the peaks in TP that are detected during the fall of 1997, 1998, and 1999. However, the model then overpredicted the peaks that occur in the fall of 2000 and 2001. It then proceeds to underestimate the whole-reservoir TP concentration during the rest of the year. DO levels appear to be predicted fairly well, with underpredictions occurring during a few years.

The Chapra and Canale Model of Horsetooth Reservoir (Figure 4.13) appeared to have a hard time predicting the timing and height of the peaks in TP concentration. This could be due to the short (~1.5 year) calibration period. Timing of reservoir turnover and stratification appears well predicted, however, the model seriously overpredicted the DO deficit that occurs in the hypolimnion during the stratified period.

As with the Chapra and Canale model of Aurora, the model of Standley Lake (Figure 4.14) was not able successfully simulate the height of the peaks in the monitoring data. Possible reasons for this are discussed in section 4.8. It also underpredicted DO concentration in the hypolimnion as it did in the other two Chapra and Canale models.

4.7 CE-QUAL-W2 Model of Aurora Reservoir



The CE-QUAL-W2 model also did a good job of predicting the peaks in whole-reservoir TP concentrations and the valleys in DO concentrations in the reservoir. The DO equations in CE-QUAL-W2 also did a better job of approximating the observed monitoring data than either of the other models because of its mechanistic approach to DO modeling.

The CE-QUAL-W2 model does not directly predict TP, a conversion is used to predict this quantity. The conversion used in this paper is the same one used by Hydrospehere (2000b) in which the model components Labile and Refractory Dissolved Organic Matter (DOM), Algae, and Labile Particulate Organic Matter (POM, a.k.a. detritus) are multiplied by a conversion factor (0.45) to predict the amount of Total Organic Carbon (TOC). TOC is then multiplied by 0.4/45 and added to Soluble Reactive Phosphorus (SRP) to get TP. The source of these conversion factors was not detailed by Hydrosphere (2000b). The TP values predicted by these conversions did a good job of matching the timing of the observed peaks and predicting average TP values. Actual peak values were close to those predicted in late summer 1997 but underestimated in late summer 1998 and 1999. Additionally, due to the two dimensional nature of CE-QUAL-W2, it should be noted that the model predictions were obtained by averaging all layers in all segments of the model to obtain a whole-reservoir TP average similar to the whole-reservoir TP values predicted by the Vollenweider and the Chapra and Canale models.

It is known that this model was calibrated by Hydrosphere (2000b), but the extent and period over which it has been calibrated is not known. Due to this limitation there will not be any comparison between validation data, but comparisons can be made to the calibration period of the Vollenweider and the Chapra and Canale models of Aurora Reservoir. These limitations also mean that we may not be using the best possible TP and DO calibration

4.8 Model Summary and Discussion

The Vollenweider model clearly showed its limitations in predicting the annual cycles in whole-reservoir phosphorus that were observed, as no peaks could be replicated with the models. However, average values can be modeled with some success by adjusting the phosphorus settling rate. The resulting calibrated models of Aurora and Horsetooth Reservoirs and Standley Lake contained phosphorus settling values that were well within those previously reported.

The Chapra and Canale model was much better at simulating the TP cycling shown in the actual reservoir data than the Vollenweider model because of the simulated release of phosphorus from the bottom sediments that occurs when the hypolimnion goes anoxic. This model required slightly more calibration than the Vollenweider model, but that was to be expected because of the model’s increased complexity and because of the limited amount of data upon which to calculate parameters. These extra calibration parameters were what allowed it to do a much better job of approximating the daily whole-reservoir TP concentrations than the Vollenweider model. However, the model seriously overestimated the HOD for Aurora and Standley, a deficiency that could be corrected with a different AHOD or VHOD regression. This may also better predict phosphorus concentrations by more accurately timing phosphorus release from the sediments.

From the graphs in the previous two sections (Figures 4.9-4.14), it appeared that the Chapra and Canale model was better at simulating the cyclical conditions in each of the three reservoirs than the Vollenweider model. However, a numerical comparison of model accuracy (Table 4.10a and Table 4.10b) showed relatively little difference between the Vollenweider and the Chapra and Canale models. The RMSE values were computed using every date in the calibration or validation period that had monitoring data available. The models of Aurora produced TP RMSE values that were roughly as large as the mean observed TP concentration and the models of Horsetooth and Standley produced TP RMSE values that were roughly half as large as the mean observed TP concentrations. This indicates that on a day-to-day basis the models were not very accurate; the error of the model was about half the value of the concentration to be predicted. The validated Vollenweider and the Chapra and Canale models did a better job of predicting the mean TP concentration for the year, returning predictions that were about 10% to 15% below the observed mean.

Table 4.10a Whole-Reservoir TP Modeling Results

Reservoir	Observed Mean TP for Period	Vollen-weider Mean TP	Vollen-weider RMSE	Chapra and Canale Mean TP	Chapra and Canale RMSE	CE-QUAL-W2 Mean TP	CE-QUAL-W2 RMSE
	Calibration Period (see Table 4.1 for exact dates)						
	(ug/L)	(ug/L)	(ug/L)	(ug/L)	(ug/L)	(ug/L)	(ug/L)
Aurora	22.3	19.7	21.1	19.3	19.0	18.1	17.9
Horsetooth	21.7	22.9	7.3	22.9	7.3	-	-
Standley	18.9	16.1	12.5	16.4	12.4	-	-

Table 4.10b Whole-Reservoir TP Modeling Results

Reservoir	Observed Mean TP for Period	Vollen-weider Mean TP	Vollen-weider RMSE	Chapra and Canale Mean TP	Chapra and Canale RMSE
	Validation Period (see Table 4.1 for exact dates)				
	(ug/L)	(ug/L)	(ug/L)	(ug/L)	(ug/L)
Aurora	16.2	26.3	18.2	10.7	15.1
Horsetooth	-	-	-	-	-
Standley	16.4	16.0	8.4	15.5	8.3

The CE-QUAL-W2 model returned values similar to those of the Vollenweider and the Chapra and Canale models, returning a mean TP that was about 20% lower than that observed. The TP RMSE was the best in the comparison. As noted before, the CE-QUAL-W2 model (Hydrosphere, 2000b) was not calibrated for this investigation; another calibration may have provided a superior data fit.

Neither the Vollenweider nor the Chapra and Canale nor the CE-QUAL-W2 model provided a reasonable fit of the data on a daily timestep, as they did not represent the peaks in TP concentrations at the end of the summer well. There are numerous reasons why these peaks were underrepresented. One reason for this could be the way in which loading to the reservoirs is represented. Currently, yearly loading is averaged to a per day basis. This is definitely not the way in which these reservoirs operate, as most of the flow to the reservoirs is provided in winter and spring, as detailed in the operational overview. In the cases of Aurora and Horsetooth Reservoirs and Standley Lake (Table 4.11), this flow provides a significant amount (20-86%) of the total phosphorus loaded into the reservoir, creating more of a pulse loading than a distributed load, which would raise the TP concentrations during this time period and for a period afterward. This reason would not apply to CE-QUAL-W2, which uses inputs on a daily timestep. Another reason for this lack of fit could be due to the use of one-location observed TP values. Due to data limitations, each reservoir was represented by multi-depth samples taken near the deepest location and averaged over depth, whereas the values predicted by the models were whole-reservoir averages. To increase the accuracy of the observed whole-reservoir mean TP, samples should be taken from shallower areas of the reservoirs on the same date as the profiles and analyzed using the same techniques.

Watershed TP loading occurs in an even more pronounced load pulse as nearly all of this load occurs during a few intense rainstorms each year, most often occurring in the summer, but sometimes in the spring or fall. The method by which these estimates are obtained is partially based on the Revised Universal Soil Loss Equation, a method that only predicts average yearly amounts of TP loading, it underestimates loads for intense events (Laflen, 2002). Better estimates for simulating event-based erosion are available using the Water Erosion Prediction Project model. 1997 is an example of a case in which annual estimates of TP loading may be off. . In July of 1997, extreme, unrelated rainfall events occurred in both the Aurora and Horsetooth Reservoir watersheds, causing severe flooding in some areas. These events likely caused significant erosion and sediment transport, however TP loading predictions from ungauged runoff (Table 4.11) were not significantly higher than for any other year in the simulation.

Table 4.11 Average TP Load Sources

Aurora Reservoir

TP Source	Units	Load	Percentage
Gauged Runoff (pipeline, wells)	kg/yr	93	17%
Ungauged Runoff (967 ha local watershed)	kg/yr	266	47%
Geese	kg/yr	34	6%
Atmospheric Depositions	kg/yr	170	30%
Total Load	kg/yr	563	100%

Horsetooth Reservoir

TP Source	Units	Load	Percentage
Gauged Runoff (canal inflow)	kg/yr	3795	81.7%
Unguaged Runoff (3870 ha local watershed)	kg/yr	378	8.1%
Shoreline Septic Systems	kg/yr	78	1.7%
Atmospheric Depositions	kg/yr	392	8.4%
Total Load	kg/yr	4643	100.0%

Standley Lake

TP Source	Units	Load	Percentage
Gauged Runoff (canal inflow)	kg/yr	3171	87.36%
Unguaged Runoff (400 ha local watershed)	kg/yr	155	4.28%
Geese	kg/yr	51	1.40%
Atmospheric Depositions	kg/yr	253	6.96%
Total Load	kg/yr	3630	100.00%

Hypolimnion DO model predictions were better than whole-reservoir TP model predictions, with RMSE values being much smaller when compared to the mean hypolimnion DO values (Table 4.12). Still, DO readings at the end of stratification were often underestimated by the models at Aurora Reservoir and Standley Lake and overestimated at Horsetooth Reservoir (Figures 4.9-4.14). This problem could be due to a number of factors. The impoundments used in the AHOD regression were all natural lakes, whereas the three impoundments being modeled were all reservoirs. Typically lakes have a bowl-shaped morphometry and reservoirs usually have more steeply sloping, incised sides as the resulting from being dammed river channels. This difference in morphometry causes the bowl-shaped impoundments to have more hypolimnion volume per unit of sediment surface than the deeply incised stream channel. This is important, as it is the sediment surface area where a majority of the oxygen demanding reactions occur. This could explain the overestimation of DO at Aurora and Standley, both of which are dams in an old, incised stream channel. The various basins that comprise Horsetooth Reservoir are more bowl-shaped in morphometry and Horsetooth has a hypolimnion volume that is half of the total reservoir volume, both of which are factors that could explain the underestimation at Horsetooth. Also, the AHOD regression does not take into account the temperature of the hypolimnion. The three reservoirs being modeled have three different hypolimnion temperatures, varying from 12 to 16° C, and the lakes from which the data was obtained likely have an even larger range. This range would cause a significant change in reaction rates in the sediment layer, which would change the rate at which oxygen was being consumed in the hypolimnion.

Table 4.12 Hypolimnion DO Modeling Results

Reservoir	Observed Mean DO for Modelled Period (ug/L)	Vollenweider Mean DO (ug/L)	Vollenweider RMSE (ug/L)	Chapra and Canale Mean DO (ug/L)	Chapra and Canale RMSE (ug/L)	CE-QUAL-W2 Mean DO (ug/L)	CE-QUAL-W2 RMSE (ug/L)
Aurora	6.4	6.1	2.5	7.0	2.2	7.4	1.8
Horsetooth	7.1	8.3	1.9	8.3	1.9	-	-
Standley	7.3	6.7	2.4	6.7	2.4	-	-

Further complicating matters, there are two primary methods of computing the Hypolimnetic Oxygen Demand, HOD. The most common method regresses HOD on the basis of the surface area of the reservoir (Areal HOD, AHOD), and is used by the models, whereas Volumetric Hypolimnetic Oxygen Demand (Volumetric HOD, VHOD) regresses HOD on the basis of hypolimnion volume. For use in reservoirs, VHOD is considered the preferable method for calculating HOD because the hypolimnion is the volume in which the oxygen depletion occurs. This volume, although variable because of fluctuations in reservoir volume, can be quantified by examination of the temperature profile. The surface area used in AHOD has no direct relation to hypolimnion volume or oxygen depletion, but it can provide a suitable estimate for oxygen depletion in natural lakes because the surface area and hypolimnion volume are both held constant by the outlet elevation and because most natural lakes are bowl-shaped, roughly relating surface area to depth.

To alleviate these problems, the AHOD equation should be calibrated to the DO data, or the monitoring data set that is being developed for each of these reservoirs could be used to obtain AHOD or VHOD regressions for each of the reservoirs. Either of these remedies would create HOD values that are more characteristic of each reservoir.

The CE-QUAL-W2 model overcomes most of the problems detailed above because it is a dynamic model with inputs that vary on a daily basis (it provides a very accurate water balance). However, in its current state of calibration, it does not provide increased accuracy in modeling whole-reservoir TP, and a much larger penalty is paid in terms of required monitoring data and model development cost and time. The implementation of the above suggestions into a Vollenweider or a Chapra and Canale type model to possibly improve results would create models that are also more demanding in terms of monitoring data and model development cost and time, eliminating some of the benefits of these models. However, as the Vollenweider and Chapra and Canale models both showed better prediction of mean whole-reservoir TP concentrations than CE-QUAL-W2, this effort may be justified.

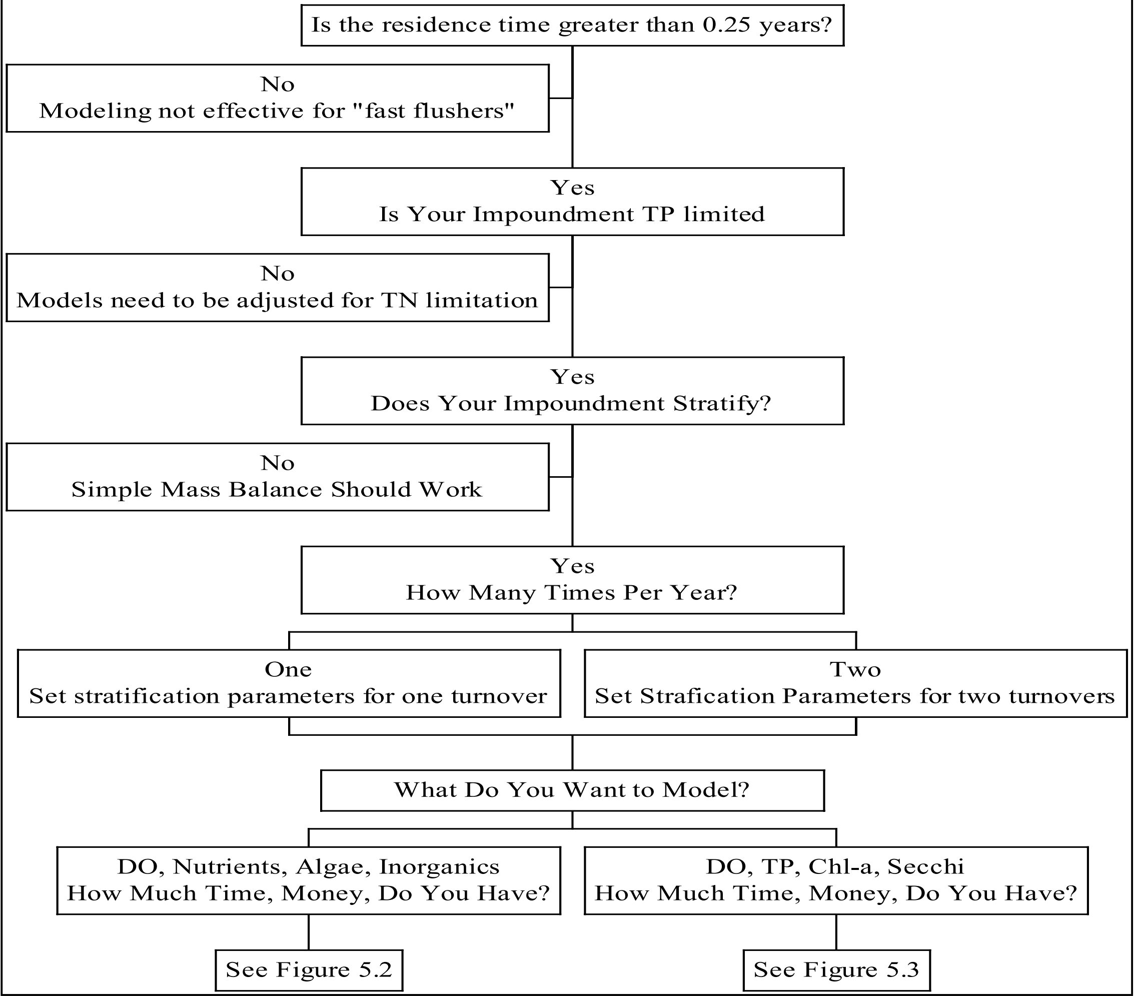
CHAPTER 5.0 DEVELOPMENT OF DECISION TREES

To aid in the application of these models to other reservoirs, a decision tree was developed. It takes into account many factors needed to select the most appropriate model for the needs. The first questions (Figure 5.1) take into account whether the reservoir to be modeled is suited to the models we have selected and include:

1. Is residence time less than 0.25 years?
2. Is the impoundment TP limited?
3. Is the reservoir stratified?
4. If the answer to 2 is yes, how many times per year?

If the answer to the first three questions is yes, the user proceeds as normal along the decision tree. If the answer to the residence time question is no, modeling in not really an effective means to solve the problem. Water is moving through the reservoir so fast that chemical reactions do not have much time to occur, meaning the impoundment is just a really slow flowing stream and water quality changes are best effected by changing upstream water quality. If the answer to the reservoir TP question is no and it is not desired that the reservoir be TP limited, e.g. nitrogen limitation is desired, the model must be reconfigured to a nitrogen mass balance approach instead of a phosphorus mass balance. If the reservoir is not stratified, a simple mass balance (e.g. Vollenweider) approach to the entire lake volume should work. In our study this would be appropriate for Horseshoe Lake and Quincy Reservoir, which are either too shallow to effectively

Figure 5.1: Model Decision Tree I



stratify or are mechanically aerated. With the fourth question for stratified reservoirs, we have a further differentiation, those that are monomictic and dimictic. The Chapra and Canale and the Vollenweider models are set up for dimictic reservoirs, but they can be easily adapted for monomictic reservoirs by changing the date at which fall stratification begins to the end of the year and the date at which stratification ends to the beginning of the year.

The next question deals (Figures 5.2 and 5.3) with what management would like the model to predict and how much time and money are available for modeling. Which of the two available options are chosen also determine to some extent what the model will require in terms of time and expense. The models that we have determined to be satisfactory for eutrophication prediction can predict the following constituents:

1. DO, nutrients, algae, inorganics (e.g. Fe, Mn)
2. TP, DO, Chlorophyll *a*, and Secchi Depth

The next question determines how much resources can be devoted to modeling with the following options:

1. < 1 Person-Year (not including monitoring)
2. > 1 Person-Year (not including monitoring)

TP, DO, Chlorophyll *a* and Secchi Depth modeling can be done with the relatively simple models that were investigated in the previous chapter. These models are not extremely resource intensive and could be developed in house if time is available. The modeling of other constituents requires the use of more complex models such as CE-QUAL-W2 and DYRESM-CAEDYM and typically requires the hiring of a consultant versed in the use of these models.

Figure 5.2: Model Decision Tree II

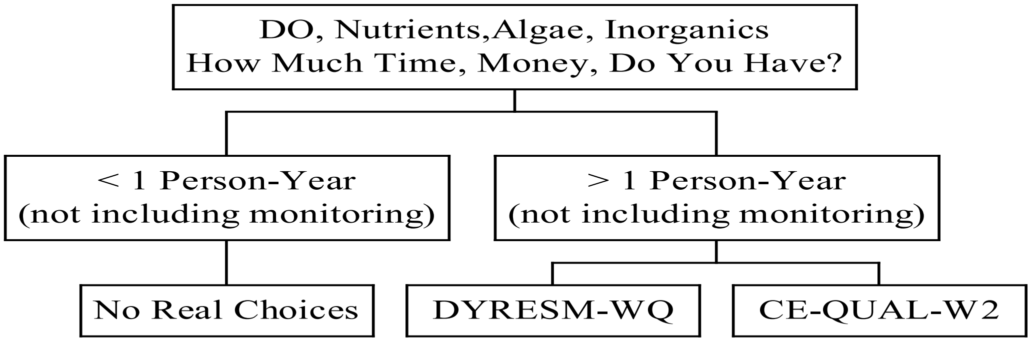
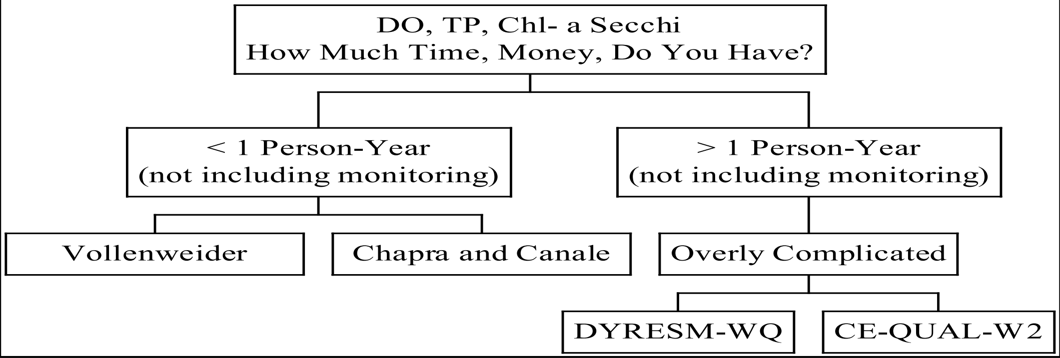


Figure 5.3: Model Decision Tree III



CHAPTER 6.0 CONCLUSIONS

When comparing model characteristics and results, the Chapra and Canale model incorporating sediment feedback appeared more favorable for implementation for most of the reservoirs looking at low cost, low time requirement solutions. It simulates the annual cycle in TP and DO that was observed in the study reservoirs but was not able to match the TP peaks found in the monitoring data. The Vollenweider model was limited in that it doesn't consider the buffering impact of sediments on TP if loading was reduced and didn't consider the effect anoxia plays in releasing phosphorus from the sediments. This limited the Vollenweider model's ability to simulate the annual TP and DO cycling. Despite the advantages of the Chapra and Canale model, both models had considerable difficulty simulating the exact daily concentration that was observed, and both appeared equally able to predict the yearly average TP concentrations within 15%.

Both models were limited by the temporal resolution of the available data, by inaccuracies in the water balance, changes in reservoir volume, and HOD estimation. Improvement in the temporal resolution of the input data would likely increase model performance, but would require much more in terms of resources for monitoring data and model development.

Of the more complex models, CE-QUAL-W2 was the only one implemented due to the excessive data input required for DYRESM-CAEDYM and the inability to obtain the code for MINLAKE. Based upon the only available comparison at Aurora Reservoir, the CE-QUAL-W2 model, as calibrated by Hydrosphere, is not recommended for TP and DO modeling due to its increased calibration and data requirements. If TP and DO modeling was all that was required from the model, it is recommended that a similarly accurate Vollenweider or Chapra and Canale model be developed. The results of this study lead to a recommendation of the Vollenweider or the Chapra and Canale models for TP and/or DO modeling. These models would also be applicable on a regional scale, as their assumptions only limit their application to Rampart Reservoir, which has such an extremely short residence time that modeling is probably not practical. The CE-QUAL-W2 model only becomes more attractive if one desires to model constituents other than TP or DO.

In addition, a decision tree was developed to aid in determination if modeling is a feasible and, if so, to help select appropriate models based on reservoir and model characteristics and availability of time and funding. This decision tree contains questions about the physical characteristics of the reservoir and the desires for the modeling program. It will be helpful for evaluating any future modeling attempts that are proposed for the reservoirs in the Front Range.

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	A	B	C	D	E	F	G	H	I	J	K	L	M
51									**QUARTERLY ANALYSIS**		Enter Start Year below		
52									**Quarter:**	**January - March**	1995		
53													
54									**Land Use**			**Runoff**	**Soil Loss**
55									**Number**	**Description**	**Area (HA)**	**Coeff**	**RE**
56									**1**	Large Lot Residential	100	0.35	0.4164
57									**2**	Rangeland	200	0.35	0.4164
58									**3**	Open Space / Parks	100	0.25	0.4164
59													
60	**Yearly Analysis**												
61	1995												
62										Mean Precipitation (cm/qtr)	2.6924		
63	**Land Use**		**TP**	**TN**	**Water**					P Enrichment	2		
64			kg	kg	m3					N Enrichment	2		
65	Rangeland		111.874	256.6995	116713					Sediment Delivery Ratio	0.25		
66	Large Lot Residential		35.98176	86.45882	223926.4								
67	Open Space / Parks		7.264442	19.45228	71920.1								
68	**Total**		155.1202	362.6106	412559.5				**RESULTS**				
69													
70									**LOADINGS / QUARTER:**		**Sediment**	**Diss P**	**Sed P**
71											**(kg/qtr)**	**(kg/qtr)**	**(kg/qtr)**
72									**1**	Rangeland	421	0.660	0.622266
73									**2**	Large Lot Residential	82	1.319	0.12185
74									**3**	Open Space / Parks	26	0.175	0.037866
75										TOTAL:	529	2.154	0.781981

	N	O	P	Q	R	S	T	U	V	W
51										
52										
53										
54	omputations					Phosphorus Concentration Estimates		Nitrogen Concentration Estimates		
55	K	LS	C	P	Xl (mT/HA)	Dissolved (mg/l)	Sed-Attached (mg/kg)	Dissolved (mg/l)	Sed-Attached (mg/kg)	
56	0.19	0.596	0.31	1	0.019	0.07	660	0.18	1500	
57	0.2	0.491	0.035	1	0.002	0.07	660	0.18	1500	
58	0.26	0.632	0.013	1	0.001	0.026	660	0.1	1500	
59										
60										
61										
62										
63										
64										
65										
66										
67										
68										
69										
70	Total P	Diss N	Sed N	Total N		Runoff				
71	(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)		m3				
72	1.281904	1.696	1.41424	3.1104524		9423.4				
73	1.441126	3.392	0.276931	3.6693548		18846.8				
74	0.212872	0.673	0.086059	0.7591588		6731				
75	2.935901	5.762	1.77723	7.538966		35001.2				

	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI
51	**QUARTERLY ANALYSIS**											
52	**Quarter:**	**April - June**	1995									
53												
54	Land Use			Runoff	Soil Loss Computations							
55	Number	Description	Area (HA)	Coeff	RE	K	LS	C	P	Xi (mT/HA)		
56	**1**	Large Lot Residential	100	0.3	26.16	0.19	0.596	0.31	1	1.185		
57	**2**	Rangeland	200	0.3	26.16	0.2	0.491	0.035	1	0.116		
58	**3**	Open Space / Parks	100	0.2	26.16	0.26	0.632	0.013	1	0.072		
59												
60												
61												
62		Mean Precipitation (cm/qtr)	26.6446									
63												
64												
65												
66												
67												
68	**RESULTS**											
69												
70	**LOADINGS / QUARTER:**		Sediment	Diss P	Sed P	Total P	Diss N	Sed N	Total N		Runoff	
71			(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)		m3	
72	**1**	Rangeland	26,468	5.595	39.09336	44.68872	14.388	88.84853	103.2366		79933.8	
73	**2**	Large Lot Residential	5,183	11.191	7.655101	18.84583	28.776	17.39796	46.17412		159867.6	
74	**3**	Open Space / Parks	1,611	1.386	2.378894	3.764414	5.329	5.406578	10.7355		53289.2	
75		TOTAL:	33,261	18.172	49.12735	67.29897	48.493	111.6531	160.1462		293090.6	

	AJ	AK	AL	AM	AN	AO	AP	AQ	AR	AS	AT	AU
51	**QUARTERLY ANALYSIS**											
52	**Quarter:**	**July - September**	1995									
53												
54	**Land Use**			**Runoff**	**Soil Loss Computations**							
55	**Number**	**Description**	**Area (HA)**	**Coeff**	**RE**	**K**	**LS**	**C**	**P**	**Xi (mT/HA)**		
56	**1**	Large Lot Residential	100	0.4	41.57	0.19	0.596	0.31	1	1.882		
57	**2**	Rangeland	200	0.3	41.57	0.2	0.491	0.035	1	0.184		
58	**3**	Open Space / Parks	100	0.15	41.57	0.26	0.632	0.01	1	0.088		
59												
60												
61												
62		Mean Precipitation (cm/qtr)	4.7498									
63												
64												
65												
66												
67												
68	**RESULTS**											
69												
70	**LOADINGS / QUARTER:**		**Sediment**	**Diss P**	**Sed P**	**Total P**	**Diss N**	**Sed N**	**Total N**		**Water**	
71			**(kg/qtr)**	**(kg/qtr)**	**(kg/qtr)**	**(kg/qtr)**	**(kg/qtr)**	**(kg/qtr)**	**(kg/qtr)**		**m3**	
72	**1**	Rangeland	42,059	1.330	62.12197	63.45192	3.420	141.1863	144.6062		18999.2	
73	**2**	Large Lot Residential	8,236	1.995	12.16447	14.15939	5.130	27.64652	32.77631		28498.8	
74	**3**	Open Space / Parks	1,969	0.185	2.907864	3.093106	0.712	6.608782	7.321252		7124.7	
75		TOTAL:	52,264	3.510	77.19431	80.70441	9.262	175.4416	184.7037		54622.7	

	AV	AW	AX	AY	AZ	BA	BB	BC	BD	BE	BF	BG
51	**QUARTERLY ANALYSIS**											
52	**Quarter:**	**October - December**	1995									
53												
54	Land Use			Runoff		Soil Loss Computations						
55	Number	Description	Area (HA)	Coeff		RE	K	LS	C	P	Xi (mT/HA)	
56	**1**	Large Lot Residential	100	0.35		1.249	0.19	0.596	0.31	1	0.057	
57	**2**	Rangeland	200	0.35		1.249	0.2	0.491	0.035	1	0.006	
58	**3**	Open Space / Parks	100	0.2		1.249	0.26	0.632	0.008	1	0.002	
59			400									
60												
61												
62		Mean Precipitation (cm/qtr)	2.3876									
63												
64												
65												
66												
67												
68	**RESULTS**											
69												
70	**LOADINGS / QUARTER:**		Sediment	Diss P		Sed P	Total P	Diss N	Sed N	Total N		Runoff
71			(kg/qtr)	(kg/qtr)		(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)		m3
72	**1**	Rangeland	1,264	0.585		1.866498	2.45146	1.504	4.242042	5.74623		8356.6
73	**2**	Large Lot Residential	247	1.170		0.36549	1.535414	3.008	0.830659	3.839035		16713.2
74	**3**	Open Space / Parks	47	0.124		0.069895	0.19405	0.478	0.158852	0.636372		4775.2
75		TOTAL:	1,558	1.879		2.301884	4.180925	4.990	5.231554	10.22164		29845

	A	B	C	D	E	F	G	H	I	J
51						**QUARTERLY ANALYSIS**		Enter Start Year below		
52						**Quarter:**	**January - March**	1995		
53										
54							**Land Use**		**Runoff**	
55						**Number**	**Description**	**Area (HA)**	**Coeff**	**RE**
56						1	Wheatland	200.6	0.35	0.4164
57						2	Rangeland	597.3	0.35	0.4164
58						3	Open Space / Parks	169.3	0.25	0.4164
59										
60	**Yearly Analysis**									
61	1995									
62							Mean Precipitation (cm/qtr)	4.0132	Obtains precip from table	
63	**Land Use**	**TP**	**TN**	**Water**			P Enrichment	2		
64		kg	kg	m3			N Enrichment	2		
65	Wheatland	133.7540808	312.8695887	424841.1112			Sediment Delivery Ratio	0.25		
66	Rangeland	141.8895432	346.7436105	1160613.63						
67	Open Space / Parks	14.44257506	41.17838437	204217.4478						
68	**Total**	290.0861991	700.7915836	1789672.189		**RESULTS**				
69										
70						**LOADINGS / QUARTER:**		**Sediment**	**Diss P**	**Sed P**
71								**(kg/qtr)**	**(kg/qtr)**	**(kg/qtr)**
72						1	Wheatland	423	1.972	0.624132587
73						2	Rangeland	246	5.873	0.363903655
74						3	Open Space / Parks	43	0.442	0.064106949
75							TOTAL:	712	8.287	1.052143191

	K	L	M	N	O	P	Q	R	S
51									
52									
53									
54		Soil Loss Computations				Phosphorus Concentration Estimates		Nitrogen Concentration Estimates	
55	K	LS	C	P	Xi (mT/HA)	Dissolved (mg/l)	Sed-Attached (mg/kg)	Dissolved (mg/l)	Sed-Attached (mg/kg)
56	0.19	0.596	0.31	0.5	0.009	0.07	660	0.18	1500
57	0.2	0.491	0.035	1	0.002	0.07	660	0.18	1500
58	0.26	0.632	0.013	1	0.001	0.026	660	0.1	1500
59									
60									
61									
62									
63									
64									
65									
66									
67									
68									
69									
70	Total P	Diss N	Sed N	Total N		Runoff			
71	(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)		m3			
72	2.5965	5.072	1.418483153	6.49029		28176.6772			
73	6.23676	15.102	0.827053762	15.9287		83897.9526			
74	0.50574	1.699	0.145697611	1.84428		16985.869			
75	9.339	21.872	2.391234526	24.2633		129060.4988			

	A	B	C	D	E	F	G	H	I	J	K	L
51												
52									**QUARTERLY ANALYSIS**		Enter Start	Year belov
53									**Quarter:**	**January - March**	1995	
54												
55									**Land Use Number**	**Description**	**Area (HA)**	**Runoff Coeff**
56									**1**		0	0.35
57									**2**	Large Lot Residential	100	0.5
58									**3**	Open Space / Parks	3770	0.25
59												
60	**Yearly Analysis**											
61	1995											
62										Mean Precipitation (cm/(	3.6576	
63	**Land Use**		**TP**	**TN**	**Water**					P Enrichment	2	
64			kg	kg	m3					N Enrichment	2	
65	0		0	0	0					Sediment Delivery Ratio	0.25	
66	Large Lot Residential		28.0757	69.1618	256032							
67	Open Space / Parks		366.5836	985.7849	3731210							
68	**Total**		394.6592	1054.947	3987242				**RESULTS**			
69												
70									**LOADINGS / QUARTER:**		**Sediment (kg/qtr)**	**Diss P (kg/qtr)**
71												
72									**1**	0	0	0.000
73									**2**	Large Lot Residential	41	1.280
74									**3**	Open Space / Parks	1,529	8.963
75										TOTAL:	1,571	10.243

	M	N	O	P	Q	R	S	T	U	V
51	√									
52										
53										
54	Soil Loss Computations						Phosphorus Concentration Estimates		Nitrogen Concentration Estimates	
55	RE	K	LS	C	P	Xi (mT/HA	Dissolved (mg/l)	Sed-Attached (mg/kg)	Dissolved (mg/l)	Sed-Attached (mg/kg)
56	0.4164	0.19	0.596	0.31	1	0.019	0.07	660	0.18	1500
57	0.4164	0.2	0.491	0.035	1	0.002	0.07	660	0.18	1500
58	0.4164	0.26	1	0.013	1	0.002	0.026	660	0.1	1500
59										
60										
61										
62										
63										
64										
65										
66										
67										
68										
69										
70	Sed P	Total P	Diss N	Sed N	Total N		Runoff			
71	(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)	(kg/qtr)		m3			
72	0	0	0.000	0	0		0			
73	0.060925	1.341085	3.292	0.138465	3.430305		18288			
74	2.258772	11.22172	34.473	5.133573	39.60645		344728.8			
75	2.319697	12.56281	37.765	5.272038	43.03676		363016.8			

APPENDIX D VOLLENWEIDER SPREADSHEET

The following pages contain example formulas for Aurora Reservoir used to implement out the Vollenweider models of the Aurora and Horsetooth Reservoirs and Standley Lake. The last two columns, AE and AF, contain the first two days of monitoring data.

	A	B	C	D	E
1	DONE				
2		DO initial	4.5	mg/L	
3		Ths	14	C	
4		Thw	4	C	
5		p settling	0.00323372365162392	/day	
6		vs	=365/(1/C5)*O20	m/yr	
7					
8					
9					
10					
11		start	35431		
12		TP initial	=Tables!AR47		
13					
14					
15					
16					
17				Loads	
18	Year	Loading Rates	Outflow	Input	Output
19			10^6 m3/yr	kg/yr	kg/yr
20	=CONCATENATE("Year"&B20+1-YEAR($C$11))	=YEAR(C11)	=VLOOKUP($B20,'AR Loads'!$E$24:$J$30,3,FALSE)/10^6	=VLOOKUP($B20,'AR Loads'!$E$24:$J$30,4,FALSE)	=C20*H20
21	=CONCATENATE("Year"&B21+1-YEAR($C$11))	=B20+1	=VLOOKUP($B21,'AR Loads'!$E$24:$J$30,3,FALSE)/10^6	=VLOOKUP($B21,'AR Loads'!$E$24:$J$30,4,FALSE)	=C21*H21
22	=CONCATENATE("Year"&B22+1-YEAR($C$11))	=B21+1	=VLOOKUP($B22,'AR Loads'!$E$24:$J$30,3,FALSE)/10^6	=VLOOKUP($B22,'AR Loads'!$E$24:$J$30,4,FALSE)	=C22*H22
23	=CONCATENATE("Year"&B23+1-YEAR($C$11))	=B22+1	=VLOOKUP($B23,'AR Loads'!$E$24:$J$30,3,FALSE)/10^6	=VLOOKUP($B23,'AR Loads'!$E$24:$J$30,4,FALSE)	=C23*H23
24	=CONCATENATE("Year"&B24+1-YEAR($C$11))	=B23+1	12	='AR Loads'!C$138	=C24*H24
25	=CONCATENATE("Year"&B25+1-YEAR($C$11))	=B24+1	12	='AR Loads'!C$138	=C25*H25
26	=CONCATENATE("Year"&B26+1-YEAR($C$11))	=B25+1	12	='AR Loads'!C$138	=C26*H26
27	=CONCATENATE("Year"&B27+1-YEAR($C$11))	=B26+1	12	='AR Loads'!C$138	=C27*H27
28	=CONCATENATE("Year"&B28+1-YEAR($C$11))	=B27+1	12	='AR Loads'!C$138	=C28*H28
29	=CONCATENATE("Year"&B29+1-YEAR($C$11))	=B28+1	12	='AR Loads'!C$138	=C29*H29
30					

Vollenweider Model Formulas

	F	G	H	I	J	K	L
1							
2	tst	1		=G2			
3	pst	130		=G3			
4	tft	285		=G4			
5	pft	365		=G5			
6	A2	=Tables!AP2(	m2				
7	z2	0.1	m				
8	V2	=G6*G7	m3				
9	Doi,s	9.55					
10	Doi,w	9.55					
11	Doa	5					
12	Out:InLake	0.93					
13							
14							
15							
16							
17		Concentrations					
18	Retained	Inflow	Outflow	In-lake (prev year)		V1 max	V1 min
19	kg/yr	mg/m3	mg/m3	mg/m3		m3	m3
20	=D20-E20	=D20/C20	=$G$12*I20	=C12		=VLOOKUP(B20,'AR Loads'!$E$24:$J$30,5,FALSE)	=VLOOKUP(B20,'AR Loads'!$E$24:$J$30,6,FALSE)
21	=D21-E21	=D21/C21	=$G$12*I21	=AVERAGE(Y3:Y368)		=VLOOKUP(B21,'AR Loads'!$E$24:$J$30,5,FALSE)	=VLOOKUP(B21,'AR Loads'!$E$24:$J$30,6,FALSE)
22	=D22-E22	=D22/C22	=$G$12*I22	=AVERAGE(Y369:Y733)		=VLOOKUP(B22,'AR Loads'!$E$24:$J$30,5,FALSE)	=VLOOKUP(B22,'AR Loads'!$E$24:$J$30,6,FALSE)
23	=D23-E23	=D23/C23	=$G$12*I23	=AVERAGE(Y734:Y1098)		=VLOOKUP(B23,'AR Loads'!$E$24:$J$30,5,FALSE)	=VLOOKUP(B23,'AR Loads'!$E$24:$J$30,6,FALSE)
24	=D24-E24	=D24/C24	=$G$12*I24	=AVERAGE(Y1099:Y1463)		=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)
25	=D25-E25	=D25/C25	=$G$12*I25	=AVERAGE(Y1464:Y1829)		=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)
26	=D26-E26	=D26/C26	=$G$12*I26	=AVERAGE(Y1830:Y2194)		=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)
27	=D27-E27	=D27/C27	=$G$12*I27	=AVERAGE(Y2195:Y2559)		=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)
28	=D28-E28	=D28/C28	=$G$12*I28	=AVERAGE(Y2560:Y2924)		=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)
29	=D29-E29	=D29/C29	=$G$12*I29	=AVERAGE(Y2925:Y3290)		=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)
30				=AVERAGE(I20:I26)			

	M	N	O	P	Q	R	S
1							
2							
3							
4							
5							
6							
7							
8							
9							
10							
11							
12							
13							
14							
15							
16							
17							
18	V1 mean	A1	z1	zh	AHODs	AHODw	ta,s
19	m3	m2	m	m	mg/m2-d	mg/m2-d	d
20	=AVERAGE(K20:L20)	=Tables!AF26	=Tables!AH26	=Tables!AS26	=0.086*I20^0.478	=Q20*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P20/Q20)
21	=AVERAGE(K21:L21)			=P$20	=0.086*I21^0.478	=Q21*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P21/Q21)
22	=AVERAGE(K22:L22)			=P$20	=0.086*I22^0.478	=Q22*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P22/Q22)
23	=AVERAGE(K23:L23)			=P$20	=0.086*I23^0.478	=Q23*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P23/Q23)
24	=AVERAGE(K24:L24)			=P$20	=0.086*I24^0.478	=Q24*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P24/Q24)
25	=AVERAGE(K25:L25)			=P$20	=0.086*I25^0.478	=Q25*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P25/Q25)
26	=AVERAGE(K26:L26)			=P$20	=0.086*I26^0.478	=Q26*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P26/Q26)
27	=AVERAGE(K27:L27)			=P$20	=0.086*I27^0.478	=Q27*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P27/Q27)
28	=AVERAGE(K28:L28)			=P$20	=0.086*I28^0.478	=Q28*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P28/Q28)
29	=AVERAGE(K29:L29)			=P$20	=0.086*I29^0.478	=Q29*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P29/Q29)
30							

Vollenweider Model Formulas

	T	U	V
1			Day
2			
3			=C11
4			=V3+1
5			=V4+1
6			=V5+1
7			=V6+1
8			=V7+1
9			=V8+1
10			=V9+1
11			=V10+1
12			=V11+1
13			=V12+1
14			=V13+1
15			=V14+1
16			=V15+1
17			=V16+1
18	ta,w		=V17+1
19	d		=V18+1
20	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P20/R20)		=V19+1
21	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P21/R21)		=V20+1
22	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P22/R22)		=V21+1
23	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P23/R23)		=V22+1
24	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P24/R24)		=V23+1
25	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P25/R25)		=V24+1
26	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P26/R26)		=V25+1
27	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P27/R27)		=V26+1
28	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P28/R28)		=V27+1
29	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P29/R29)		=V28+1
30			=V29+1

	W
1	Jday
2	
3	=CHOOSE(MONTH(V3),0+DAY(V3),31+DAY(V3),59+DAY(V3),90+DAY(V3),120+DAY(V3),151+DAY(V3),181+DAY(V3),212+DAY(V3),243+DAY(V3),273+DAY(V3),304+DAY(V3),334+DAY(V3))
4	=CHOOSE(MONTH(V4),0+DAY(V4),31+DAY(V4),59+DAY(V4),90+DAY(V4),120+DAY(V4),151+DAY(V4),181+DAY(V4),212+DAY(V4),243+DAY(V4),273+DAY(V4),304+DAY(V4),334+DAY(V4))
5	=CHOOSE(MONTH(V5),0+DAY(V5),31+DAY(V5),59+DAY(V5),90+DAY(V5),120+DAY(V5),151+DAY(V5),181+DAY(V5),212+DAY(V5),243+DAY(V5),273+DAY(V5),304+DAY(V5),334+DAY(V5))
6	=CHOOSE(MONTH(V6),0+DAY(V6),31+DAY(V6),59+DAY(V6),90+DAY(V6),120+DAY(V6),151+DAY(V6),181+DAY(V6),212+DAY(V6),243+DAY(V6),273+DAY(V6),304+DAY(V6),334+DAY(V6))
7	=CHOOSE(MONTH(V7),0+DAY(V7),31+DAY(V7),59+DAY(V7),90+DAY(V7),120+DAY(V7),151+DAY(V7),181+DAY(V7),212+DAY(V7),243+DAY(V7),273+DAY(V7),304+DAY(V7),334+DAY(V7))
8	=CHOOSE(MONTH(V8),0+DAY(V8),31+DAY(V8),59+DAY(V8),90+DAY(V8),120+DAY(V8),151+DAY(V8),181+DAY(V8),212+DAY(V8),243+DAY(V8),273+DAY(V8),304+DAY(V8),334+DAY(V8))
9	=CHOOSE(MONTH(V9),0+DAY(V9),31+DAY(V9),59+DAY(V9),90+DAY(V9),120+DAY(V9),151+DAY(V9),181+DAY(V9),212+DAY(V9),243+DAY(V9),273+DAY(V9),304+DAY(V9),334+DAY(V9))
10	=CHOOSE(MONTH(V10),0+DAY(V10),31+DAY(V10),59+DAY(V10),90+DAY(V10),120+DAY(V10),151+DAY(V10),181+DAY(V10),212+DAY(V10),243+DAY(V10),273+DAY(V10),304+DAY(V10),334+DAY(V10))
11	=CHOOSE(MONTH(V11),0+DAY(V11),31+DAY(V11),59+DAY(V11),90+DAY(V11),120+DAY(V11),151+DAY(V11),181+DAY(V11),212+DAY(V11),243+DAY(V11),273+DAY(V11),304+DAY(V11),334+DAY(V11))
12	=CHOOSE(MONTH(V12),0+DAY(V12),31+DAY(V12),59+DAY(V12),90+DAY(V12),120+DAY(V12),151+DAY(V12),181+DAY(V12),212+DAY(V12),243+DAY(V12),273+DAY(V12),304+DAY(V12),334+DAY(V12))
13	=CHOOSE(MONTH(V13),0+DAY(V13),31+DAY(V13),59+DAY(V13),90+DAY(V13),120+DAY(V13),151+DAY(V13),181+DAY(V13),212+DAY(V13),243+DAY(V13),273+DAY(V13),304+DAY(V13),334+DAY(V13))
14	=CHOOSE(MONTH(V14),0+DAY(V14),31+DAY(V14),59+DAY(V14),90+DAY(V14),120+DAY(V14),151+DAY(V14),181+DAY(V14),212+DAY(V14),243+DAY(V14),273+DAY(V14),304+DAY(V14),334+DAY(V14))
15	=CHOOSE(MONTH(V15),0+DAY(V15),31+DAY(V15),59+DAY(V15),90+DAY(V15),120+DAY(V15),151+DAY(V15),181+DAY(V15),212+DAY(V15),243+DAY(V15),273+DAY(V15),304+DAY(V15),334+DAY(V15))
16	=CHOOSE(MONTH(V16),0+DAY(V16),31+DAY(V16),59+DAY(V16),90+DAY(V16),120+DAY(V16),151+DAY(V16),181+DAY(V16),212+DAY(V16),243+DAY(V16),273+DAY(V16),304+DAY(V16),334+DAY(V16))
17	=CHOOSE(MONTH(V17),0+DAY(V17),31+DAY(V17),59+DAY(V17),90+DAY(V17),120+DAY(V17),151+DAY(V17),181+DAY(V17),212+DAY(V17),243+DAY(V17),273+DAY(V17),304+DAY(V17),334+DAY(V17))
18	=CHOOSE(MONTH(V18),0+DAY(V18),31+DAY(V18),59+DAY(V18),90+DAY(V18),120+DAY(V18),151+DAY(V18),181+DAY(V18),212+DAY(V18),243+DAY(V18),273+DAY(V18),304+DAY(V18),334+DAY(V18))
19	=CHOOSE(MONTH(V19),0+DAY(V19),31+DAY(V19),59+DAY(V19),90+DAY(V19),120+DAY(V19),151+DAY(V19),181+DAY(V19),212+DAY(V19),243+DAY(V19),273+DAY(V19),304+DAY(V19),334+DAY(V19))
20	=CHOOSE(MONTH(V20),0+DAY(V20),31+DAY(V20),59+DAY(V20),90+DAY(V20),120+DAY(V20),151+DAY(V20),181+DAY(V20),212+DAY(V20),243+DAY(V20),273+DAY(V20),304+DAY(V20),334+DAY(V20))
21	=CHOOSE(MONTH(V21),0+DAY(V21),31+DAY(V21),59+DAY(V21),90+DAY(V21),120+DAY(V21),151+DAY(V21),181+DAY(V21),212+DAY(V21),243+DAY(V21),273+DAY(V21),304+DAY(V21),334+DAY(V21))
22	=CHOOSE(MONTH(V22),0+DAY(V22),31+DAY(V22),59+DAY(V22),90+DAY(V22),120+DAY(V22),151+DAY(V22),181+DAY(V22),212+DAY(V22),243+DAY(V22),273+DAY(V22),304+DAY(V22),334+DAY(V22))
23	=CHOOSE(MONTH(V23),0+DAY(V23),31+DAY(V23),59+DAY(V23),90+DAY(V23),120+DAY(V23),151+DAY(V23),181+DAY(V23),212+DAY(V23),243+DAY(V23),273+DAY(V23),304+DAY(V23),334+DAY(V23))
24	=CHOOSE(MONTH(V24),0+DAY(V24),31+DAY(V24),59+DAY(V24),90+DAY(V24),120+DAY(V24),151+DAY(V24),181+DAY(V24),212+DAY(V24),243+DAY(V24),273+DAY(V24),304+DAY(V24),334+DAY(V24))
25	=CHOOSE(MONTH(V25),0+DAY(V25),31+DAY(V25),59+DAY(V25),90+DAY(V25),120+DAY(V25),151+DAY(V25),181+DAY(V25),212+DAY(V25),243+DAY(V25),273+DAY(V25),304+DAY(V25),334+DAY(V25))
26	=CHOOSE(MONTH(V26),0+DAY(V26),31+DAY(V26),59+DAY(V26),90+DAY(V26),120+DAY(V26),151+DAY(V26),181+DAY(V26),212+DAY(V26),243+DAY(V26),273+DAY(V26),304+DAY(V26),334+DAY(V26))
27	=CHOOSE(MONTH(V27),0+DAY(V27),31+DAY(V27),59+DAY(V27),90+DAY(V27),120+DAY(V27),151+DAY(V27),181+DAY(V27),212+DAY(V27),243+DAY(V27),273+DAY(V27),304+DAY(V27),334+DAY(V27))
28	=CHOOSE(MONTH(V28),0+DAY(V28),31+DAY(V28),59+DAY(V28),90+DAY(V28),120+DAY(V28),151+DAY(V28),181+DAY(V28),212+DAY(V28),243+DAY(V28),273+DAY(V28),304+DAY(V28),334+DAY(V28))
29	=CHOOSE(MONTH(V29),0+DAY(V29),31+DAY(V29),59+DAY(V29),90+DAY(V29),120+DAY(V29),151+DAY(V29),181+DAY(V29),212+DAY(V29),243+DAY(V29),273+DAY(V29),304+DAY(V29),334+DAY(V29))
30	=CHOOSE(MONTH(V30),0+DAY(V30),31+DAY(V30),59+DAY(V30),90+DAY(V30),120+DAY(V30),151+DAY(V30),181+DAY(V30),212+DAY(V30),243+DAY(V30),273+DAY(V30),304+DAY(V30),334+DAY(V30))

	X
1	Year
2	
3	=CONCATENATE("Year",YEAR(V3)+1-$B$20)
4	=CONCATENATE("Year",YEAR(V4)+1-$B$20)
5	=CONCATENATE("Year",YEAR(V5)+1-$B$20)
6	=CONCATENATE("Year",YEAR(V6)+1-$B$20)
7	=CONCATENATE("Year",YEAR(V7)+1-$B$20)
8	=CONCATENATE("Year",YEAR(V8)+1-$B$20)
9	=CONCATENATE("Year",YEAR(V9)+1-$B$20)
10	=CONCATENATE("Year",YEAR(V10)+1-$B$20)
11	=CONCATENATE("Year",YEAR(V11)+1-$B$20)
12	=CONCATENATE("Year",YEAR(V12)+1-$B$20)
13	=CONCATENATE("Year",YEAR(V13)+1-$B$20)
14	=CONCATENATE("Year",YEAR(V14)+1-$B$20)
15	=CONCATENATE("Year",YEAR(V15)+1-$B$20)
16	=CONCATENATE("Year",YEAR(V16)+1-$B$20)
17	=CONCATENATE("Year",YEAR(V17)+1-$B$20)
18	=CONCATENATE("Year",YEAR(V18)+1-$B$20)
19	=CONCATENATE("Year",YEAR(V19)+1-$B$20)
20	=CONCATENATE("Year",YEAR(V20)+1-$B$20)
21	=CONCATENATE("Year",YEAR(V21)+1-$B$20)
22	=CONCATENATE("Year",YEAR(V22)+1-$B$20)
23	=CONCATENATE("Year",YEAR(V23)+1-$B$20)
24	=CONCATENATE("Year",YEAR(V24)+1-$B$20)
25	=CONCATENATE("Year",YEAR(V25)+1-$B$20)
26	=CONCATENATE("Year",YEAR(V26)+1-$B$20)
27	=CONCATENATE("Year",YEAR(V27)+1-$B$20)
28	=CONCATENATE("Year",YEAR(V28)+1-$B$20)
29	=CONCATENATE("Year",YEAR(V29)+1-$B$20)
30	=CONCATENATE("Year",YEAR(V30)+1-$B$20)

	Y
1	LakeTP
2	=1.25*C12
3	=Y2+(VLOOKUP(X3,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X3,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y2-$C$6*$G$6*Y2)/(VLOOKUP(X3,$A$20:$T$83,13,FALSE)*365)
4	=Y3+(VLOOKUP(X4,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X4,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y3-$C$6*$G$6*Y3)/(VLOOKUP(X4,$A$20:$T$83,13,FALSE)*365)
5	=Y4+(VLOOKUP(X5,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X5,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y4-$C$6*$G$6*Y4)/(VLOOKUP(X5,$A$20:$T$83,13,FALSE)*365)
6	=Y5+(VLOOKUP(X6,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X6,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y5-$C$6*$G$6*Y5)/(VLOOKUP(X6,$A$20:$T$83,13,FALSE)*365)
7	=Y6+(VLOOKUP(X7,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X7,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y6-$C$6*$G$6*Y6)/(VLOOKUP(X7,$A$20:$T$83,13,FALSE)*365)
8	=Y7+(VLOOKUP(X8,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X8,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y7-$C$6*$G$6*Y7)/(VLOOKUP(X8,$A$20:$T$83,13,FALSE)*365)
9	=Y8+(VLOOKUP(X9,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X9,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y8-$C$6*$G$6*Y8)/(VLOOKUP(X9,$A$20:$T$83,13,FALSE)*365)
10	=Y9+(VLOOKUP(X10,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X10,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y9-$C$6*$G$6*Y9)/(VLOOKUP(X10,$A$20:$T$83,13,FALSE)*365)
11	=Y10+(VLOOKUP(X11,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X11,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y10-$C$6*$G$6*Y10)/(VLOOKUP(X11,$A$20:$T$83,13,FALSE)*365)
12	=Y11+(VLOOKUP(X12,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X12,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y11-$C$6*$G$6*Y11)/(VLOOKUP(X12,$A$20:$T$83,13,FALSE)*365)
13	=Y12+(VLOOKUP(X13,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X13,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y12-$C$6*$G$6*Y12)/(VLOOKUP(X13,$A$20:$T$83,13,FALSE)*365)
14	=Y13+(VLOOKUP(X14,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X14,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y13-$C$6*$G$6*Y13)/(VLOOKUP(X14,$A$20:$T$83,13,FALSE)*365)
15	=Y14+(VLOOKUP(X15,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X15,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y14-$C$6*$G$6*Y14)/(VLOOKUP(X15,$A$20:$T$83,13,FALSE)*365)
16	=Y15+(VLOOKUP(X16,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X16,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y15-$C$6*$G$6*Y15)/(VLOOKUP(X16,$A$20:$T$83,13,FALSE)*365)
17	=Y16+(VLOOKUP(X17,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X17,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y16-$C$6*$G$6*Y16)/(VLOOKUP(X17,$A$20:$T$83,13,FALSE)*365)
18	=Y17+(VLOOKUP(X18,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X18,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y17-$C$6*$G$6*Y17)/(VLOOKUP(X18,$A$20:$T$83,13,FALSE)*365)
19	=Y18+(VLOOKUP(X19,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X19,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y18-$C$6*$G$6*Y18)/(VLOOKUP(X19,$A$20:$T$83,13,FALSE)*365)
20	=Y19+(VLOOKUP(X20,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X20,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y19-$C$6*$G$6*Y19)/(VLOOKUP(X20,$A$20:$T$83,13,FALSE)*365)
21	=Y20+(VLOOKUP(X21,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X21,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y20-$C$6*$G$6*Y20)/(VLOOKUP(X21,$A$20:$T$83,13,FALSE)*365)
22	=Y21+(VLOOKUP(X22,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X22,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y21-$C$6*$G$6*Y21)/(VLOOKUP(X22,$A$20:$T$83,13,FALSE)*365)
23	=Y22+(VLOOKUP(X23,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X23,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y22-$C$6*$G$6*Y22)/(VLOOKUP(X23,$A$20:$T$83,13,FALSE)*365)
24	=Y23+(VLOOKUP(X24,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X24,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y23-$C$6*$G$6*Y23)/(VLOOKUP(X24,$A$20:$T$83,13,FALSE)*365)
25	=Y24+(VLOOKUP(X25,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X25,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y24-$C$6*$G$6*Y24)/(VLOOKUP(X25,$A$20:$T$83,13,FALSE)*365)
26	=Y25+(VLOOKUP(X26,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X26,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y25-$C$6*$G$6*Y25)/(VLOOKUP(X26,$A$20:$T$83,13,FALSE)*365)
27	=Y26+(VLOOKUP(X27,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X27,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y26-$C$6*$G$6*Y26)/(VLOOKUP(X27,$A$20:$T$83,13,FALSE)*365)
28	=Y27+(VLOOKUP(X28,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X28,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y27-$C$6*$G$6*Y27)/(VLOOKUP(X28,$A$20:$T$83,13,FALSE)*365)
29	=Y28+(VLOOKUP(X29,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X29,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y28-$C$6*$G$6*Y28)/(VLOOKUP(X29,$A$20:$T$83,13,FALSE)*365)
30	=Y29+(VLOOKUP(X30,$A$20:$T$83,4,FALSE)*10^6-VLOOKUP(X30,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y29-$C$6*$G$6*Y29)/(VLOOKUP(X30,$A$20:$T$83,13,FALSE)*365)

	Z	AA
1	Doi	DO f
2	9.55	
3	=Z2	=IF((Z3-AB3/$P$20)>0,Z3-(AB3/$P$20),0)
4	=IF(AND($G$2<=W4,W4<$G$3),$G$9,IF(AND($G$4<=W4,W4<$G$5),$G$10,AA3))	=IF((Z4-AB4/$P$20)>0,Z4-(AB4/$P$20),0)
5	=IF(AND($G$2<=W5,W5<$G$3),$G$9,IF(AND($G$4<=W5,W5<$G$5),$G$10,AA4))	=IF((Z5-AB5/$P$20)>0,Z5-(AB5/$P$20),0)
6	=IF(AND($G$2<=W6,W6<$G$3),$G$9,IF(AND($G$4<=W6,W6<$G$5),$G$10,AA5))	=IF((Z6-AB6/$P$20)>0,Z6-(AB6/$P$20),0)
7	=IF(AND($G$2<=W7,W7<$G$3),$G$9,IF(AND($G$4<=W7,W7<$G$5),$G$10,AA6))	=IF((Z7-AB7/$P$20)>0,Z7-(AB7/$P$20),0)
8	=IF(AND($G$2<=W8,W8<$G$3),$G$9,IF(AND($G$4<=W8,W8<$G$5),$G$10,AA7))	=IF((Z8-AB8/$P$20)>0,Z8-(AB8/$P$20),0)
9	=IF(AND($G$2<=W9,W9<$G$3),$G$9,IF(AND($G$4<=W9,W9<$G$5),$G$10,AA8))	=IF((Z9-AB9/$P$20)>0,Z9-(AB9/$P$20),0)
10	=IF(AND($G$2<=W10,W10<$G$3),$G$9,IF(AND($G$4<=W10,W10<$G$5),$G$10,AA9))	=IF((Z10-AB10/$P$20)>0,Z10-(AB10/$P$20),0)
11	=IF(AND($G$2<=W11,W11<$G$3),$G$9,IF(AND($G$4<=W11,W11<$G$5),$G$10,AA10))	=IF((Z11-AB11/$P$20)>0,Z11-(AB11/$P$20),0)
12	=IF(AND($G$2<=W12,W12<$G$3),$G$9,IF(AND($G$4<=W12,W12<$G$5),$G$10,AA11))	=IF((Z12-AB12/$P$20)>0,Z12-(AB12/$P$20),0)
13	=IF(AND($G$2<=W13,W13<$G$3),$G$9,IF(AND($G$4<=W13,W13<$G$5),$G$10,AA12))	=IF((Z13-AB13/$P$20)>0,Z13-(AB13/$P$20),0)
14	=IF(AND($G$2<=W14,W14<$G$3),$G$9,IF(AND($G$4<=W14,W14<$G$5),$G$10,AA13))	=IF((Z14-AB14/$P$20)>0,Z14-(AB14/$P$20),0)
15	=IF(AND($G$2<=W15,W15<$G$3),$G$9,IF(AND($G$4<=W15,W15<$G$5),$G$10,AA14))	=IF((Z15-AB15/$P$20)>0,Z15-(AB15/$P$20),0)
16	=IF(AND($G$2<=W16,W16<$G$3),$G$9,IF(AND($G$4<=W16,W16<$G$5),$G$10,AA15))	=IF((Z16-AB16/$P$20)>0,Z16-(AB16/$P$20),0)
17	=IF(AND($G$2<=W17,W17<$G$3),$G$9,IF(AND($G$4<=W17,W17<$G$5),$G$10,AA16))	=IF((Z17-AB17/$P$20)>0,Z17-(AB17/$P$20),0)
18	=IF(AND($G$2<=W18,W18<$G$3),$G$9,IF(AND($G$4<=W18,W18<$G$5),$G$10,AA17))	=IF((Z18-AB18/$P$20)>0,Z18-(AB18/$P$20),0)
19	=IF(AND($G$2<=W19,W19<$G$3),$G$9,IF(AND($G$4<=W19,W19<$G$5),$G$10,AA18))	=IF((Z19-AB19/$P$20)>0,Z19-(AB19/$P$20),0)
20	=IF(AND($G$2<=W20,W20<$G$3),$G$9,IF(AND($G$4<=W20,W20<$G$5),$G$10,AA19))	=IF((Z20-AB20/$P$20)>0,Z20-(AB20/$P$20),0)
21	=IF(AND($G$2<=W21,W21<$G$3),$G$9,IF(AND($G$4<=W21,W21<$G$5),$G$10,AA20))	=IF((Z21-AB21/$P$20)>0,Z21-(AB21/$P$20),0)
22	=IF(AND($G$2<=W22,W22<$G$3),$G$9,IF(AND($G$4<=W22,W22<$G$5),$G$10,AA21))	=IF((Z22-AB22/$P$20)>0,Z22-(AB22/$P$20),0)
23	=IF(AND($G$2<=W23,W23<$G$3),$G$9,IF(AND($G$4<=W23,W23<$G$5),$G$10,AA22))	=IF((Z23-AB23/$P$20)>0,Z23-(AB23/$P$20),0)
24	=IF(AND($G$2<=W24,W24<$G$3),$G$9,IF(AND($G$4<=W24,W24<$G$5),$G$10,AA23))	=IF((Z24-AB24/$P$20)>0,Z24-(AB24/$P$20),0)
25	=IF(AND($G$2<=W25,W25<$G$3),$G$9,IF(AND($G$4<=W25,W25<$G$5),$G$10,AA24))	=IF((Z25-AB25/$P$20)>0,Z25-(AB25/$P$20),0)
26	=IF(AND($G$2<=W26,W26<$G$3),$G$9,IF(AND($G$4<=W26,W26<$G$5),$G$10,AA25))	=IF((Z26-AB26/$P$20)>0,Z26-(AB26/$P$20),0)
27	=IF(AND($G$2<=W27,W27<$G$3),$G$9,IF(AND($G$4<=W27,W27<$G$5),$G$10,AA26))	=IF((Z27-AB27/$P$20)>0,Z27-(AB27/$P$20),0)
28	=IF(AND($G$2<=W28,W28<$G$3),$G$9,IF(AND($G$4<=W28,W28<$G$5),$G$10,AA27))	=IF((Z28-AB28/$P$20)>0,Z28-(AB28/$P$20),0)
29	=IF(AND($G$2<=W29,W29<$G$3),$G$9,IF(AND($G$4<=W29,W29<$G$5),$G$10,AA28))	=IF((Z29-AB29/$P$20)>0,Z29-(AB29/$P$20),0)
30	=IF(AND($G$2<=W30,W30<$G$3),$G$9,IF(AND($G$4<=W30,W30<$G$5),$G$10,AA29))	=IF((Z30-AB30/$P$20)>0,Z30-(AB30/$P$20),0)

Vollenweider Model Formulas

	AB	AC	AD
1	AHOD		
2			
3	=IF(OR(W3<=$G$2,W3>$G$5),VLOOKUP($X3,$A$20:$T$83,18,FALSE),VLOOKUP($X3,$A$20:$T$83,17,FALSE))		Day
4	=IF(OR(W4<=$G$2,W4>$G$5),VLOOKUP($X4,$A$20:$T$83,18,FALSE),VLOOKUP($X4,$A$20:$T$83,17,FALSE))		Observed
5	=IF(OR(W5<=$G$2,W5>$G$5),VLOOKUP($X5,$A$20:$T$83,18,FALSE),VLOOKUP($X5,$A$20:$T$83,17,FALSE))		Mean Observed
6	=IF(OR(W6<=$G$2,W6>$G$5),VLOOKUP($X6,$A$20:$T$83,18,FALSE),VLOOKUP($X6,$A$20:$T$83,17,FALSE))		Model
7	=IF(OR(W7<=$G$2,W7>$G$5),VLOOKUP($X7,$A$20:$T$83,18,FALSE),VLOOKUP($X7,$A$20:$T$83,17,FALSE))		Error^2
8	=IF(OR(W8<=$G$2,W8>$G$5),VLOOKUP($X8,$A$20:$T$83,18,FALSE),VLOOKUP($X8,$A$20:$T$83,17,FALSE))		RMSE (calibration)
9	=IF(OR(W9<=$G$2,W9>$G$5),VLOOKUP($X9,$A$20:$T$83,18,FALSE),VLOOKUP($X9,$A$20:$T$83,17,FALSE))		RMSE (validation)
10	=IF(OR(W10<=$G$2,W10>$G$5),VLOOKUP($X10,$A$20:$T$83,18,FALSE),VLOOKUP($X10,$A$20:$T$83,17,FALSE))		Mean model (calibration)
11	=IF(OR(W11<=$G$2,W11>$G$5),VLOOKUP($X11,$A$20:$T$83,18,FALSE),VLOOKUP($X11,$A$20:$T$83,17,FALSE))		Mean model (validation)
12	=IF(OR(W12<=$G$2,W12>$G$5),VLOOKUP($X12,$A$20:$T$83,18,FALSE),VLOOKUP($X12,$A$20:$T$83,17,FALSE))		
13	=IF(OR(W13<=$G$2,W13>$G$5),VLOOKUP($X13,$A$20:$T$83,18,FALSE),VLOOKUP($X13,$A$20:$T$83,17,FALSE))		
14	=IF(OR(W14<=$G$2,W14>$G$5),VLOOKUP($X14,$A$20:$T$83,18,FALSE),VLOOKUP($X14,$A$20:$T$83,17,FALSE))		Observed
15	=IF(OR(W15<=$G$2,W15>$G$5),VLOOKUP($X15,$A$20:$T$83,18,FALSE),VLOOKUP($X15,$A$20:$T$83,17,FALSE))		Mean Observed
16	=IF(OR(W16<=$G$2,W16>$G$5),VLOOKUP($X16,$A$20:$T$83,18,FALSE),VLOOKUP($X16,$A$20:$T$83,17,FALSE))		Model
17	=IF(OR(W17<=$G$2,W17>$G$5),VLOOKUP($X17,$A$20:$T$83,18,FALSE),VLOOKUP($X17,$A$20:$T$83,17,FALSE))		Error^2
18	=IF(OR(W18<=$G$2,W18>$G$5),VLOOKUP($X18,$A$20:$T$83,18,FALSE),VLOOKUP($X18,$A$20:$T$83,17,FALSE))		RMSE
19	=IF(OR(W19<=$G$2,W19>$G$5),VLOOKUP($X19,$A$20:$T$83,18,FALSE),VLOOKUP($X19,$A$20:$T$83,17,FALSE))		Mean model
20	=IF(OR(W20<=$G$2,W20>$G$5),VLOOKUP($X20,$A$20:$T$83,18,FALSE),VLOOKUP($X20,$A$20:$T$83,17,FALSE))		
21	=IF(OR(W21<=$G$2,W21>$G$5),VLOOKUP($X21,$A$20:$T$83,18,FALSE),VLOOKUP($X21,$A$20:$T$83,17,FALSE))		
22	=IF(OR(W22<=$G$2,W22>$G$5),VLOOKUP($X22,$A$20:$T$83,18,FALSE),VLOOKUP($X22,$A$20:$T$83,17,FALSE))		
23	=IF(OR(W23<=$G$2,W23>$G$5),VLOOKUP($X23,$A$20:$T$83,18,FALSE),VLOOKUP($X23,$A$20:$T$83,17,FALSE))		
24	=IF(OR(W24<=$G$2,W24>$G$5),VLOOKUP($X24,$A$20:$T$83,18,FALSE),VLOOKUP($X24,$A$20:$T$83,17,FALSE))		
25	=IF(OR(W25<=$G$2,W25>$G$5),VLOOKUP($X25,$A$20:$T$83,18,FALSE),VLOOKUP($X25,$A$20:$T$83,17,FALSE))		
26	=IF(OR(W26<=$G$2,W26>$G$5),VLOOKUP($X26,$A$20:$T$83,18,FALSE),VLOOKUP($X26,$A$20:$T$83,17,FALSE))		
27	=IF(OR(W27<=$G$2,W27>$G$5),VLOOKUP($X27,$A$20:$T$83,18,FALSE),VLOOKUP($X27,$A$20:$T$83,17,FALSE))		
28	=IF(OR(W28<=$G$2,W28>$G$5),VLOOKUP($X28,$A$20:$T$83,18,FALSE),VLOOKUP($X28,$A$20:$T$83,17,FALSE))		
29	=IF(OR(W29<=$G$2,W29>$G$5),VLOOKUP($X29,$A$20:$T$83,18,FALSE),VLOOKUP($X29,$A$20:$T$83,17,FALSE))		
30	=IF(OR(W30<=$G$2,W30>$G$5),VLOOKUP($X30,$A$20:$T$83,18,FALSE),VLOOKUP($X30,$A$20:$T$83,17,FALSE))		

	AE	AF
1	**AR TP Data**	
2		
3	35542	35598
4	16	12
5	=AVERAGE(AE4:CZ4)	
6	=VLOOKUP(AE3,'VM AR'!$V$3:$AB$3655,4,FALSE)	=VLOOKUP(AF3,'VM AR'!$V$3:$AB$3655,4,FALSE)
7	=(AE6-AE4)^2	=(AF6-AF4)^2
8	=SQRT(SUM(AE7:BH7)/30)	
9	=SQRT(SUM(BH7:CZ7)/45)	
10	=AVERAGE(AE6:BH6)	
11	=AVERAGE(BI6:CZ6)	
12	**AR DO Data**	
13	35535	35542
14	10.7	10.4
15	=AVERAGE(AE14:DA14)	
16	=VLOOKUP(AE13,'VM AR'!$V$3:$AB$3655,5,FALSE)	=VLOOKUP(AF13,'VM AR'!$V$3:$AB$3655,5,FALSE)
17	=(AE16-AE14)^2	=(AF16-AF14)^2
18	=SQRT(AVERAGE(AE17:DA17))	
19	=AVERAGE(AE16:DA16)	
20		
21		
22		
23		
24		
25		
26		
27		
28		
29		
30		

APPENDIX E CHAPRA AND CANALE SPREADSHEET

The following pages contain example formulas for Aurora Reservoir used to implement out the Chapra and Canale models of the Aurora and Horsetooth Reservoirs and Standley Lake. The last two columns, AG and AH, contain the first two days of monitoring data. Cell Y3 is too large to display at once, it should read:

```
=IF(AA3>$G$11,Y2+(VLOOKUP(X3,$A$20:$T$83,4,FALSE)*10^6-
VLOOKUP(X3,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y2-
$C$6*$G$6*Y2)/(VLOOKUP(X3,$A$20:$T$83,13,FALSE)*365),Y2+(VLOOKUP(X3,
$A$20:$T$83,4,FALSE)*10^6-
VLOOKUP(X3,$A$20:$T$83,3,FALSE)*10^6*$G$12*Y2-
$C$6*$G$6*Y2+AD3*$G$6*Z2)/((VLOOKUP(X3,$A$20:$T$83,13,FALSE)*365)))
```

	A	B	C	D	E	F
1	DONE					
2		DO initial	4.5	mg/L		tst
3		Ths	14	C		pst
4		Thw	4	C		tft
5		p settling	0.0384	/day		pft
6		vs	=365/(1/C5)*O20	m/yr		A2
7		vb	0.002631	m/yr		z2
8		vr	0.22452506829193	m/yr		V2
9		vr s	=C8*1.08^(C3-20)	m/yr		Doi,s
10		vr w	=C8*1.08^(C4-20)	m/yr		Doi,w
11		start	35431			Doa
12		TP initial	=Tables!AR47			Out:InLake
13						
14						
15						
16						
17				Loads		
18	Year	Loading Rates	Outflow	Input	Output	Retained
19			10^6 m3/yr	kg/yr	kg/yr	kg/yr
20	=CONCATENATE("Year"&B20+1-YEAR($C$11))	=YEAR(C11)	=VLOOKUP($B20,'AR Loads'!$E$24:$J$30,3,FALSE)/10^6	=VLOOKUP($B20,'AR Loads'!$E$24:$J$30,4,FALSE)	=C20*H20	=D20-E20
21	=CONCATENATE("Year"&B21+1-YEAR($C$11))	=B20+1	=VLOOKUP($B21,'AR Loads'!$E$24:$J$30,3,FALSE)/10^6	=VLOOKUP($B21,'AR Loads'!$E$24:$J$30,4,FALSE)	=C21*H21	=D21-E21
22	=CONCATENATE("Year"&B22+1-YEAR($C$11))	=B21+1	=VLOOKUP($B22,'AR Loads'!$E$24:$J$30,3,FALSE)/10^6	=VLOOKUP($B22,'AR Loads'!$E$24:$J$30,4,FALSE)	=C22*H22	=D22-E22
23	=CONCATENATE("Year"&B23+1-YEAR($C$11))	=B22+1	=VLOOKUP($B23,'AR Loads'!$E$24:$J$30,3,FALSE)/10^6	=VLOOKUP($B23,'AR Loads'!$E$24:$J$30,4,FALSE)	=C23*H23	=D23-E23
24	=CONCATENATE("Year"&B24+1-YEAR($C$11))	=B23+1	12	='AR Loads'!C$138	=C24*H24	=D24-E24
25	=CONCATENATE("Year"&B25+1-YEAR($C$11))	=B24+1	12	='AR Loads'!C$138	=C25*H25	=D25-E25
26	=CONCATENATE("Year"&B26+1-YEAR($C$11))	=B25+1	12	='AR Loads'!C$138	=C26*H26	=D26-E26
27	=CONCATENATE("Year"&B27+1-YEAR($C$11))	=B26+1	12	='AR Loads'!C$138	=C27*H27	=D27-E27
28	=CONCATENATE("Year"&B28+1-YEAR($C$11))	=B27+1	12	='AR Loads'!C$138	=C28*H28	=D28-E28
29	=CONCATENATE("Year"&B29+1-YEAR($C$11))	=B28+1	12	='AR Loads'!C$138	=C29*H29	=D29-E29
30						

Chapra and Canale Model Formulas

	G	H	I	J	K	L	M
1							
2	1		=G2				
3	130		=G3				
4	285		=G4				
5	365		=G5				
6	=Tables!AP26	m2					
7	0.1						
8	=G6*G7	m3					
9	9.55						
10	9.55						
11	5						
12	0.93						
13							
14							
15							
16							
17	Concentrations						
18	Inflow	Outflow	In-lake	Sediment	V1 max	V1 min	V1 mean
19	mg/m3	mg/m3	mg/m3		m3	m3	m3
20	=D20/C20	=$G$12*I20	=C12	100000	=VLOOKUP(B20,'AR Loads'!$E$24:$J$30,5,FALSE)	=VLOOKUP(B20,'AR Loads'!$E$24:$J$30,6,FALSE)	=AVERAGE(K20:L20)
21	=D21/C21	=$G$12*I21	=AVERAGE(Y3:Y368)	=AVERAGE(Z3:Z368)	=VLOOKUP(B21,'AR Loads'!$E$24:$J$30,5,FALSE)	=VLOOKUP(B21,'AR Loads'!$E$24:$J$30,6,FALSE)	=AVERAGE(K21:L21)
22	=D22/C22	=$G$12*I22	=AVERAGE(Y369:Y733)	=AVERAGE(Z369:Z733)	=VLOOKUP(B22,'AR Loads'!$E$24:$J$30,5,FALSE)	=VLOOKUP(B22,'AR Loads'!$E$24:$J$30,6,FALSE)	=AVERAGE(K22:L22)
23	=D23/C23	=$G$12*I23	=AVERAGE(Y734:Y1098)	=AVERAGE(Z734:Z1098)	=VLOOKUP(B23,'AR Loads'!$E$24:$J$30,5,FALSE)	=VLOOKUP(B23,'AR Loads'!$E$24:$J$30,6,FALSE)	=AVERAGE(K23:L23)
24	=D24/C24	=$G$12*I24	=AVERAGE(Y1099:Y1463)	=AVERAGE(Z1099:Z1463)	=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)	=AVERAGE(K24:L24)
25	=D25/C25	=$G$12*I25	=AVERAGE(Y1464:Y1829)	=AVERAGE(Z1464:Z1829)	=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)	=AVERAGE(K25:L25)
26	=D26/C26	=$G$12*I26	=AVERAGE(Y1830:Y2194)	=AVERAGE(Z1830:Z2194)	=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)	=AVERAGE(K26:L26)
27	=D27/C27	=$G$12*I27	=AVERAGE(Y2195:Y2559)	=AVERAGE(Z2195:Z2559)	=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)	=AVERAGE(K27:L27)
28	=D28/C28	=$G$12*I28	=AVERAGE(Y2560:Y2924)	=AVERAGE(Z2560:Z2924)	=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)	=AVERAGE(K28:L28)
29	=D29/C29	=$G$12*I29	=AVERAGE(Y2925:Y3290)	=AVERAGE(Z2925:Z3290)	=AVERAGE('AR Loads'!I$25:I$30)	=AVERAGE('AR Loads'!J$25:J$30)	=AVERAGE(K29:L29)
30			=AVERAGE(I20:I26)				

	N	O	P	Q	R	S	T	U	V
1									Day
2									
3									=C11
4									=V3+1
5									=V4+1
6									=V5+1
7									=V6+1
8									=V7+1
9									=V8+1
10									=V9+1
11									=V10+1
12									=V11+1
13									=V12+1
14									=V13+1
15									=V14+1
16									=V15+1
17	Lake SA	Ave Depth	Hypo Depth						=V16+1
18	A1	z1	zh	AHODs	AHODw	ta,s	ta,w		=V17+1
19	m2	m	m	mg/m2-d	mg/m2-d	d	d		=V18+1
20	=Tables!AF26	=Tables!AH26	=Tables!AS26	=0.086*I20^0.478	=Q20*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P20/Q20)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P20/R20)		=V19+1
21			=P$20	=0.086*I21^0.478	=Q21*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P21/Q21)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P21/R21)		=V20+1
22			=P$20	=0.086*I22^0.478	=Q22*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P22/Q22)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P22/R22)		=V21+1
23			=P$20	=0.086*I23^0.478	=Q23*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P23/Q23)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P23/R23)		=V22+1
24			=P$20	=0.086*I24^0.478	=Q24*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P24/Q24)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P24/R24)		=V23+1
25			=P$20	=0.086*I25^0.478	=Q25*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P25/Q25)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P25/R25)		=V24+1
26			=P$20	=0.086*I26^0.478	=Q26*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P26/Q26)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P26/R26)		=V25+1
27			=P$20	=0.086*I27^0.478	=Q27*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P27/Q27)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P27/R27)		=V26+1
28			=P$20	=0.086*I28^0.478	=Q28*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P28/Q28)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P28/R28)		=V27+1
29			=P$20	=0.086*I29^0.478	=Q29*1.08^($C$4-$C$3)	=($G$4-$G$3)-(($G$9-$G$11)*P29/Q29)	=((365-$G$5)+$G$2-0)-(($G$10-$G$11)*P29/R29)		=V28+1
30									=V29+1

Chapra and Canale Model Formulas

	W
1	Jday
2	
3	=CHOOSE(MONTH(V3),0+DAY(V3),31+DAY(V3),59+DAY(V3),90+DAY(V3),120+DAY(V3),151+DAY(V3),181+DAY(V3),212+DAY(V3),243+DAY(V3),273+DAY(V3),304+DAY(V3),334+DAY(V3))
4	=CHOOSE(MONTH(V4),0+DAY(V4),31+DAY(V4),59+DAY(V4),90+DAY(V4),120+DAY(V4),151+DAY(V4),181+DAY(V4),212+DAY(V4),243+DAY(V4),273+DAY(V4),304+DAY(V4),334+DAY(V4))
5	=CHOOSE(MONTH(V5),0+DAY(V5),31+DAY(V5),59+DAY(V5),90+DAY(V5),120+DAY(V5),151+DAY(V5),181+DAY(V5),212+DAY(V5),243+DAY(V5),273+DAY(V5),304+DAY(V5),334+DAY(V5))
6	=CHOOSE(MONTH(V6),0+DAY(V6),31+DAY(V6),59+DAY(V6),90+DAY(V6),120+DAY(V6),151+DAY(V6),181+DAY(V6),212+DAY(V6),243+DAY(V6),273+DAY(V6),304+DAY(V6),334+DAY(V6))
7	=CHOOSE(MONTH(V7),0+DAY(V7),31+DAY(V7),59+DAY(V7),90+DAY(V7),120+DAY(V7),151+DAY(V7),181+DAY(V7),212+DAY(V7),243+DAY(V7),273+DAY(V7),304+DAY(V7),334+DAY(V7))
8	=CHOOSE(MONTH(V8),0+DAY(V8),31+DAY(V8),59+DAY(V8),90+DAY(V8),120+DAY(V8),151+DAY(V8),181+DAY(V8),212+DAY(V8),243+DAY(V8),273+DAY(V8),304+DAY(V8),334+DAY(V8))
9	=CHOOSE(MONTH(V9),0+DAY(V9),31+DAY(V9),59+DAY(V9),90+DAY(V9),120+DAY(V9),151+DAY(V9),181+DAY(V9),212+DAY(V9),243+DAY(V9),273+DAY(V9),304+DAY(V9),334+DAY(V9))
10	=CHOOSE(MONTH(V10),0+DAY(V10),31+DAY(V10),59+DAY(V10),90+DAY(V10),120+DAY(V10),151+DAY(V10),181+DAY(V10),212+DAY(V10),243+DAY(V10),273+DAY(V10),304+DAY(V10),334+DAY(V10))
11	=CHOOSE(MONTH(V11),0+DAY(V11),31+DAY(V11),59+DAY(V11),90+DAY(V11),120+DAY(V11),151+DAY(V11),181+DAY(V11),212+DAY(V11),243+DAY(V11),273+DAY(V11),304+DAY(V11),334+DAY(V11))
12	=CHOOSE(MONTH(V12),0+DAY(V12),31+DAY(V12),59+DAY(V12),90+DAY(V12),120+DAY(V12),151+DAY(V12),181+DAY(V12),212+DAY(V12),243+DAY(V12),273+DAY(V12),304+DAY(V12),334+DAY(V12))
13	=CHOOSE(MONTH(V13),0+DAY(V13),31+DAY(V13),59+DAY(V13),90+DAY(V13),120+DAY(V13),151+DAY(V13),181+DAY(V13),212+DAY(V13),243+DAY(V13),273+DAY(V13),304+DAY(V13),334+DAY(V13))
14	=CHOOSE(MONTH(V14),0+DAY(V14),31+DAY(V14),59+DAY(V14),90+DAY(V14),120+DAY(V14),151+DAY(V14),181+DAY(V14),212+DAY(V14),243+DAY(V14),273+DAY(V14),304+DAY(V14),334+DAY(V14))
15	=CHOOSE(MONTH(V15),0+DAY(V15),31+DAY(V15),59+DAY(V15),90+DAY(V15),120+DAY(V15),151+DAY(V15),181+DAY(V15),212+DAY(V15),243+DAY(V15),273+DAY(V15),304+DAY(V15),334+DAY(V15))
16	=CHOOSE(MONTH(V16),0+DAY(V16),31+DAY(V16),59+DAY(V16),90+DAY(V16),120+DAY(V16),151+DAY(V16),181+DAY(V16),212+DAY(V16),243+DAY(V16),273+DAY(V16),304+DAY(V16),334+DAY(V16))
17	=CHOOSE(MONTH(V17),0+DAY(V17),31+DAY(V17),59+DAY(V17),90+DAY(V17),120+DAY(V17),151+DAY(V17),181+DAY(V17),212+DAY(V17),243+DAY(V17),273+DAY(V17),304+DAY(V17),334+DAY(V17))
18	=CHOOSE(MONTH(V18),0+DAY(V18),31+DAY(V18),59+DAY(V18),90+DAY(V18),120+DAY(V18),151+DAY(V18),181+DAY(V18),212+DAY(V18),243+DAY(V18),273+DAY(V18),304+DAY(V18),334+DAY(V18))
19	=CHOOSE(MONTH(V19),0+DAY(V19),31+DAY(V19),59+DAY(V19),90+DAY(V19),120+DAY(V19),151+DAY(V19),181+DAY(V19),212+DAY(V19),243+DAY(V19),273+DAY(V19),304+DAY(V19),334+DAY(V19))
20	=CHOOSE(MONTH(V20),0+DAY(V20),31+DAY(V20),59+DAY(V20),90+DAY(V20),120+DAY(V20),151+DAY(V20),181+DAY(V20),212+DAY(V20),243+DAY(V20),273+DAY(V20),304+DAY(V20),334+DAY(V20))
21	=CHOOSE(MONTH(V21),0+DAY(V21),31+DAY(V21),59+DAY(V21),90+DAY(V21),120+DAY(V21),151+DAY(V21),181+DAY(V21),212+DAY(V21),243+DAY(V21),273+DAY(V21),304+DAY(V21),334+DAY(V21))
22	=CHOOSE(MONTH(V22),0+DAY(V22),31+DAY(V22),59+DAY(V22),90+DAY(V22),120+DAY(V22),151+DAY(V22),181+DAY(V22),212+DAY(V22),243+DAY(V22),273+DAY(V22),304+DAY(V22),334+DAY(V22))
23	=CHOOSE(MONTH(V23),0+DAY(V23),31+DAY(V23),59+DAY(V23),90+DAY(V23),120+DAY(V23),151+DAY(V23),181+DAY(V23),212+DAY(V23),243+DAY(V23),273+DAY(V23),304+DAY(V23),334+DAY(V23))
24	=CHOOSE(MONTH(V24),0+DAY(V24),31+DAY(V24),59+DAY(V24),90+DAY(V24),120+DAY(V24),151+DAY(V24),181+DAY(V24),212+DAY(V24),243+DAY(V24),273+DAY(V24),304+DAY(V24),334+DAY(V24))
25	=CHOOSE(MONTH(V25),0+DAY(V25),31+DAY(V25),59+DAY(V25),90+DAY(V25),120+DAY(V25),151+DAY(V25),181+DAY(V25),212+DAY(V25),243+DAY(V25),273+DAY(V25),304+DAY(V25),334+DAY(V25))
26	=CHOOSE(MONTH(V26),0+DAY(V26),31+DAY(V26),59+DAY(V26),90+DAY(V26),120+DAY(V26),151+DAY(V26),181+DAY(V26),212+DAY(V26),243+DAY(V26),273+DAY(V26),304+DAY(V26),334+DAY(V26))
27	=CHOOSE(MONTH(V27),0+DAY(V27),31+DAY(V27),59+DAY(V27),90+DAY(V27),120+DAY(V27),151+DAY(V27),181+DAY(V27),212+DAY(V27),243+DAY(V27),273+DAY(V27),304+DAY(V27),334+DAY(V27))
28	=CHOOSE(MONTH(V28),0+DAY(V28),31+DAY(V28),59+DAY(V28),90+DAY(V28),120+DAY(V28),151+DAY(V28),181+DAY(V28),212+DAY(V28),243+DAY(V28),273+DAY(V28),304+DAY(V28),334+DAY(V28))
29	=CHOOSE(MONTH(V29),0+DAY(V29),31+DAY(V29),59+DAY(V29),90+DAY(V29),120+DAY(V29),151+DAY(V29),181+DAY(V29),212+DAY(V29),243+DAY(V29),273+DAY(V29),304+DAY(V29),334+DAY(V29))
30	=CHOOSE(MONTH(V30),0+DAY(V30),31+DAY(V30),59+DAY(V30),90+DAY(V30),120+DAY(V30),151+DAY(V30),181+DAY(V30),212+DAY(V30),243+DAY(V30),273+DAY(V30),304+DAY(V30),334+DAY(V30))

	X	Y	Z
1	Year	LakeP	p2
2		=C13*C12	=J20
3	=CONCATENATE("Year",YEAR(V3)+1-$B$20)	=IF(AA3>$G$11,Y2+(VL	=IF(AA3>$G$11,Z2+($C$6*$G$6*Y2-$C$7*$G$6*Z2)/($G$8*365),Z2+($C$6*$G$6*Y2-AD3*$G$6*Z2-$C$7*$G$6*Z2)/($G$8*365))
4	=CONCATENATE("Year",YEAR(V4)+1-$B$20)	=IF(AA4>$G$11,Y3+(VL	=IF(AA4>$G$11,Z3+($C$6*$G$6*Y3-$C$7*$G$6*Z3)/($G$8*365),Z3+($C$6*$G$6*Y3-AD4*$G$6*Z3-$C$7*$G$6*Z3)/($G$8*365))
5	=CONCATENATE("Year",YEAR(V5)+1-$B$20)	=IF(AA5>$G$11,Y4+(VL	=IF(AA5>$G$11,Z4+($C$6*$G$6*Y4-$C$7*$G$6*Z4)/($G$8*365),Z4+($C$6*$G$6*Y4-AD5*$G$6*Z4-$C$7*$G$6*Z4)/($G$8*365))
6	=CONCATENATE("Year",YEAR(V6)+1-$B$20)	=IF(AA6>$G$11,Y5+(VL	=IF(AA6>$G$11,Z5+($C$6*$G$6*Y5-$C$7*$G$6*Z5)/($G$8*365),Z5+($C$6*$G$6*Y5-AD6*$G$6*Z5-$C$7*$G$6*Z5)/($G$8*365))
7	=CONCATENATE("Year",YEAR(V7)+1-$B$20)	=IF(AA7>$G$11,Y6+(VL	=IF(AA7>$G$11,Z6+($C$6*$G$6*Y6-$C$7*$G$6*Z6)/($G$8*365),Z6+($C$6*$G$6*Y6-AD7*$G$6*Z6-$C$7*$G$6*Z6)/($G$8*365))
8	=CONCATENATE("Year",YEAR(V8)+1-$B$20)	=IF(AA8>$G$11,Y7+(VL	=IF(AA8>$G$11,Z7+($C$6*$G$6*Y7-$C$7*$G$6*Z7)/($G$8*365),Z7+($C$6*$G$6*Y7-AD8*$G$6*Z7-$C$7*$G$6*Z7)/($G$8*365))
9	=CONCATENATE("Year",YEAR(V9)+1-$B$20)	=IF(AA9>$G$11,Y8+(VL	=IF(AA9>$G$11,Z8+($C$6*$G$6*Y8-$C$7*$G$6*Z8)/($G$8*365),Z8+($C$6*$G$6*Y8-AD9*$G$6*Z8-$C$7*$G$6*Z8)/($G$8*365))
10	=CONCATENATE("Year",YEAR(V10)+1-$B$20)	=IF(AA10>$G$11,Y9+(VL	=IF(AA10>$G$11,Z9+($C$6*$G$6*Y9-$C$7*$G$6*Z9)/($G$8*365),Z9+($C$6*$G$6*Y9-AD10*$G$6*Z9-$C$7*$G$6*Z9)/($G$8*365))
11	=CONCATENATE("Year",YEAR(V11)+1-$B$20)	=IF(AA11>$G$11,Y10+(V	=IF(AA11>$G$11,Z10+($C$6*$G$6*Y10-$C$7*$G$6*Z10)/($G$8*365),Z10+($C$6*$G$6*Y10-AD11*$G$6*Z10-$C$7*$G$6*Z10)/($G$8*365))
12	=CONCATENATE("Year",YEAR(V12)+1-$B$20)	=IF(AA12>$G$11,Y11+(V	=IF(AA12>$G$11,Z11+($C$6*$G$6*Y11-$C$7*$G$6*Z11)/($G$8*365),Z11+($C$6*$G$6*Y11-AD12*$G$6*Z11-$C$7*$G$6*Z11)/($G$8*365))
13	=CONCATENATE("Year",YEAR(V13)+1-$B$20)	=IF(AA13>$G$11,Y12+(V	=IF(AA13>$G$11,Z12+($C$6*$G$6*Y12-$C$7*$G$6*Z12)/($G$8*365),Z12+($C$6*$G$6*Y12-AD13*$G$6*Z12-$C$7*$G$6*Z12)/($G$8*365))
14	=CONCATENATE("Year",YEAR(V14)+1-$B$20)	=IF(AA14>$G$11,Y13+(V	=IF(AA14>$G$11,Z13+($C$6*$G$6*Y13-$C$7*$G$6*Z13)/($G$8*365),Z13+($C$6*$G$6*Y13-AD14*$G$6*Z13-$C$7*$G$6*Z13)/($G$8*365))
15	=CONCATENATE("Year",YEAR(V15)+1-$B$20)	=IF(AA15>$G$11,Y14+(V	=IF(AA15>$G$11,Z14+($C$6*$G$6*Y14-$C$7*$G$6*Z14)/($G$8*365),Z14+($C$6*$G$6*Y14-AD15*$G$6*Z14-$C$7*$G$6*Z14)/($G$8*365))
16	=CONCATENATE("Year",YEAR(V16)+1-$B$20)	=IF(AA16>$G$11,Y15+(V	=IF(AA16>$G$11,Z15+($C$6*$G$6*Y15-$C$7*$G$6*Z15)/($G$8*365),Z15+($C$6*$G$6*Y15-AD16*$G$6*Z15-$C$7*$G$6*Z15)/($G$8*365))
17	=CONCATENATE("Year",YEAR(V17)+1-$B$20)	=IF(AA17>$G$11,Y16+(V	=IF(AA17>$G$11,Z16+($C$6*$G$6*Y16-$C$7*$G$6*Z16)/($G$8*365),Z16+($C$6*$G$6*Y16-AD17*$G$6*Z16-$C$7*$G$6*Z16)/($G$8*365))
18	=CONCATENATE("Year",YEAR(V18)+1-$B$20)	=IF(AA18>$G$11,Y17+(V	=IF(AA18>$G$11,Z17+($C$6*$G$6*Y17-$C$7*$G$6*Z17)/($G$8*365),Z17+($C$6*$G$6*Y17-AD18*$G$6*Z17-$C$7*$G$6*Z17)/($G$8*365))
19	=CONCATENATE("Year",YEAR(V19)+1-$B$20)	=IF(AA19>$G$11,Y18+(V	=IF(AA19>$G$11,Z18+($C$6*$G$6*Y18-$C$7*$G$6*Z18)/($G$8*365),Z18+($C$6*$G$6*Y18-AD19*$G$6*Z18-$C$7*$G$6*Z18)/($G$8*365))
20	=CONCATENATE("Year",YEAR(V20)+1-$B$20)	=IF(AA20>$G$11,Y19+(V	=IF(AA20>$G$11,Z19+($C$6*$G$6*Y19-$C$7*$G$6*Z19)/($G$8*365),Z19+($C$6*$G$6*Y19-AD20*$G$6*Z19-$C$7*$G$6*Z19)/($G$8*365))
21	=CONCATENATE("Year",YEAR(V21)+1-$B$20)	=IF(AA21>$G$11,Y20+(V	=IF(AA21>$G$11,Z20+($C$6*$G$6*Y20-$C$7*$G$6*Z20)/($G$8*365),Z20+($C$6*$G$6*Y20-AD21*$G$6*Z20-$C$7*$G$6*Z20)/($G$8*365))
22	=CONCATENATE("Year",YEAR(V22)+1-$B$20)	=IF(AA22>$G$11,Y21+(V	=IF(AA22>$G$11,Z21+($C$6*$G$6*Y21-$C$7*$G$6*Z21)/($G$8*365),Z21+($C$6*$G$6*Y21-AD22*$G$6*Z21-$C$7*$G$6*Z21)/($G$8*365))
23	=CONCATENATE("Year",YEAR(V23)+1-$B$20)	=IF(AA23>$G$11,Y22+(V	=IF(AA23>$G$11,Z22+($C$6*$G$6*Y22-$C$7*$G$6*Z22)/($G$8*365),Z22+($C$6*$G$6*Y22-AD23*$G$6*Z22-$C$7*$G$6*Z22)/($G$8*365))
24	=CONCATENATE("Year",YEAR(V24)+1-$B$20)	=IF(AA24>$G$11,Y23+(V	=IF(AA24>$G$11,Z23+($C$6*$G$6*Y23-$C$7*$G$6*Z23)/($G$8*365),Z23+($C$6*$G$6*Y23-AD24*$G$6*Z23-$C$7*$G$6*Z23)/($G$8*365))
25	=CONCATENATE("Year",YEAR(V25)+1-$B$20)	=IF(AA25>$G$11,Y24+(V	=IF(AA25>$G$11,Z24+($C$6*$G$6*Y24-$C$7*$G$6*Z24)/($G$8*365),Z24+($C$6*$G$6*Y24-AD25*$G$6*Z24-$C$7*$G$6*Z24)/($G$8*365))
26	=CONCATENATE("Year",YEAR(V26)+1-$B$20)	=IF(AA26>$G$11,Y25+(V	=IF(AA26>$G$11,Z25+($C$6*$G$6*Y25-$C$7*$G$6*Z25)/($G$8*365),Z25+($C$6*$G$6*Y25-AD26*$G$6*Z25-$C$7*$G$6*Z25)/($G$8*365))
27	=CONCATENATE("Year",YEAR(V27)+1-$B$20)	=IF(AA27>$G$11,Y26+(V	=IF(AA27>$G$11,Z26+($C$6*$G$6*Y26-$C$7*$G$6*Z26)/($G$8*365),Z26+($C$6*$G$6*Y26-AD27*$G$6*Z26-$C$7*$G$6*Z26)/($G$8*365))
28	=CONCATENATE("Year",YEAR(V28)+1-$B$20)	=IF(AA28>$G$11,Y27+(V	=IF(AA28>$G$11,Z27+($C$6*$G$6*Y27-$C$7*$G$6*Z27)/($G$8*365),Z27+($C$6*$G$6*Y27-AD28*$G$6*Z27-$C$7*$G$6*Z27)/($G$8*365))
29	=CONCATENATE("Year",YEAR(V29)+1-$B$20)	=IF(AA29>$G$11,Y28+(V	=IF(AA29>$G$11,Z28+($C$6*$G$6*Y28-$C$7*$G$6*Z28)/($G$8*365),Z28+($C$6*$G$6*Y28-AD29*$G$6*Z28-$C$7*$G$6*Z28)/($G$8*365))
30	=CONCATENATE("Year",YEAR(V30)+1-$B$20)	=IF(AA30>$G$11,Y29+(V	=IF(AA30>$G$11,Z29+($C$6*$G$6*Y29-$C$7*$G$6*Z29)/($G$8*365),Z29+($C$6*$G$6*Y29-AD30*$G$6*Z29-$C$7*$G$6*Z29)/($G$8*365))

Chapra and Canale Model Formulas

	AA	AB
1	Doi	DO f
2	9.55	
3	=AA2	=IF((AA3-AC3/$P$20)>0,AA3-(AC3/$P$20),0)
4	=IF(AND($G$2<=W4,W4<$G$3),$G$9,IF(AND($G$4<=W4,W4<$G$5),$G$10,AB3))	=IF((AA4-AC4/$P$20)>0,AA4-(AC4/$P$20),0)
5	=IF(AND($G$2<=W5,W5<$G$3),$G$9,IF(AND($G$4<=W5,W5<$G$5),$G$10,AB4))	=IF((AA5-AC5/$P$20)>0,AA5-(AC5/$P$20),0)
6	=IF(AND($G$2<=W6,W6<$G$3),$G$9,IF(AND($G$4<=W6,W6<$G$5),$G$10,AB5))	=IF((AA6-AC6/$P$20)>0,AA6-(AC6/$P$20),0)
7	=IF(AND($G$2<=W7,W7<$G$3),$G$9,IF(AND($G$4<=W7,W7<$G$5),$G$10,AB6))	=IF((AA7-AC7/$P$20)>0,AA7-(AC7/$P$20),0)
8	=IF(AND($G$2<=W8,W8<$G$3),$G$9,IF(AND($G$4<=W8,W8<$G$5),$G$10,AB7))	=IF((AA8-AC8/$P$20)>0,AA8-(AC8/$P$20),0)
9	=IF(AND($G$2<=W9,W9<$G$3),$G$9,IF(AND($G$4<=W9,W9<$G$5),$G$10,AB8))	=IF((AA9-AC9/$P$20)>0,AA9-(AC9/$P$20),0)
10	=IF(AND($G$2<=W10,W10<$G$3),$G$9,IF(AND($G$4<=W10,W10<$G$5),$G$10,AB9))	=IF((AA10-AC10/$P$20)>0,AA10-(AC10/$P$20),0)
11	=IF(AND($G$2<=W11,W11<$G$3),$G$9,IF(AND($G$4<=W11,W11<$G$5),$G$10,AB10))	=IF((AA11-AC11/$P$20)>0,AA11-(AC11/$P$20),0)
12	=IF(AND($G$2<=W12,W12<$G$3),$G$9,IF(AND($G$4<=W12,W12<$G$5),$G$10,AB11))	=IF((AA12-AC12/$P$20)>0,AA12-(AC12/$P$20),0)
13	=IF(AND($G$2<=W13,W13<$G$3),$G$9,IF(AND($G$4<=W13,W13<$G$5),$G$10,AB12))	=IF((AA13-AC13/$P$20)>0,AA13-(AC13/$P$20),0)
14	=IF(AND($G$2<=W14,W14<$G$3),$G$9,IF(AND($G$4<=W14,W14<$G$5),$G$10,AB13))	=IF((AA14-AC14/$P$20)>0,AA14-(AC14/$P$20),0)
15	=IF(AND($G$2<=W15,W15<$G$3),$G$9,IF(AND($G$4<=W15,W15<$G$5),$G$10,AB14))	=IF((AA15-AC15/$P$20)>0,AA15-(AC15/$P$20),0)
16	=IF(AND($G$2<=W16,W16<$G$3),$G$9,IF(AND($G$4<=W16,W16<$G$5),$G$10,AB15))	=IF((AA16-AC16/$P$20)>0,AA16-(AC16/$P$20),0)
17	=IF(AND($G$2<=W17,W17<$G$3),$G$9,IF(AND($G$4<=W17,W17<$G$5),$G$10,AB16))	=IF((AA17-AC17/$P$20)>0,AA17-(AC17/$P$20),0)
18	=IF(AND($G$2<=W18,W18<$G$3),$G$9,IF(AND($G$4<=W18,W18<$G$5),$G$10,AB17))	=IF((AA18-AC18/$P$20)>0,AA18-(AC18/$P$20),0)
19	=IF(AND($G$2<=W19,W19<$G$3),$G$9,IF(AND($G$4<=W19,W19<$G$5),$G$10,AB18))	=IF((AA19-AC19/$P$20)>0,AA19-(AC19/$P$20),0)
20	=IF(AND($G$2<=W20,W20<$G$3),$G$9,IF(AND($G$4<=W20,W20<$G$5),$G$10,AB19))	=IF((AA20-AC20/$P$20)>0,AA20-(AC20/$P$20),0)
21	=IF(AND($G$2<=W21,W21<$G$3),$G$9,IF(AND($G$4<=W21,W21<$G$5),$G$10,AB20))	=IF((AA21-AC21/$P$20)>0,AA21-(AC21/$P$20),0)
22	=IF(AND($G$2<=W22,W22<$G$3),$G$9,IF(AND($G$4<=W22,W22<$G$5),$G$10,AB21))	=IF((AA22-AC22/$P$20)>0,AA22-(AC22/$P$20),0)
23	=IF(AND($G$2<=W23,W23<$G$3),$G$9,IF(AND($G$4<=W23,W23<$G$5),$G$10,AB22))	=IF((AA23-AC23/$P$20)>0,AA23-(AC23/$P$20),0)
24	=IF(AND($G$2<=W24,W24<$G$3),$G$9,IF(AND($G$4<=W24,W24<$G$5),$G$10,AB23))	=IF((AA24-AC24/$P$20)>0,AA24-(AC24/$P$20),0)
25	=IF(AND($G$2<=W25,W25<$G$3),$G$9,IF(AND($G$4<=W25,W25<$G$5),$G$10,AB24))	=IF((AA25-AC25/$P$20)>0,AA25-(AC25/$P$20),0)
26	=IF(AND($G$2<=W26,W26<$G$3),$G$9,IF(AND($G$4<=W26,W26<$G$5),$G$10,AB25))	=IF((AA26-AC26/$P$20)>0,AA26-(AC26/$P$20),0)
27	=IF(AND($G$2<=W27,W27<$G$3),$G$9,IF(AND($G$4<=W27,W27<$G$5),$G$10,AB26))	=IF((AA27-AC27/$P$20)>0,AA27-(AC27/$P$20),0)
28	=IF(AND($G$2<=W28,W28<$G$3),$G$9,IF(AND($G$4<=W28,W28<$G$5),$G$10,AB27))	=IF((AA28-AC28/$P$20)>0,AA28-(AC28/$P$20),0)
29	=IF(AND($G$2<=W29,W29<$G$3),$G$9,IF(AND($G$4<=W29,W29<$G$5),$G$10,AB28))	=IF((AA29-AC29/$P$20)>0,AA29-(AC29/$P$20),0)
30	=IF(AND($G$2<=W30,W30<$G$3),$G$9,IF(AND($G$4<=W30,W30<$G$5),$G$10,AB29))	=IF((AA30-AC30/$P$20)>0,AA30-(AC30/$P$20),0)

Chapra and Canale Model Formulas

	AC	AD	AE	AF
1	AHOD	vr		
2				
3	=IF(OR(W3<=$G$2,W3>$G$5),VLOOKUP($X3,$A$20:$T$83,18,FALSE),VLOOKUP($X3,$A$20:$T$83,17,FALSE))	=IF(OR(W3<=$G$2,W3>$G$5),$C$10,$C$9)		
4	=IF(OR(W4<=$G$2,W4>$G$5),VLOOKUP($X4,$A$20:$T$83,18,FALSE),VLOOKUP($X4,$A$20:$T$83,17,FALSE))	=IF(OR(W4<=$G$2,W4>$G$5),$C$10,$C$9)		Actual
5	=IF(OR(W5<=$G$2,W5>$G$5),VLOOKUP($X5,$A$20:$T$83,18,FALSE),VLOOKUP($X5,$A$20:$T$83,17,FALSE))	=IF(OR(W5<=$G$2,W5>$G$5),$C$10,$C$9)		
6	=IF(OR(W6<=$G$2,W6>$G$5),VLOOKUP($X6,$A$20:$T$83,18,FALSE),VLOOKUP($X6,$A$20:$T$83,17,FALSE))	=IF(OR(W6<=$G$2,W6>$G$5),$C$10,$C$9)		Model
7	=IF(OR(W7<=$G$2,W7>$G$5),VLOOKUP($X7,$A$20:$T$83,18,FALSE),VLOOKUP($X7,$A$20:$T$83,17,FALSE))	=IF(OR(W7<=$G$2,W7>$G$5),$C$10,$C$9)		Error^2
8	=IF(OR(W8<=$G$2,W8>$G$5),VLOOKUP($X8,$A$20:$T$83,18,FALSE),VLOOKUP($X8,$A$20:$T$83,17,FALSE))	=IF(OR(W8<=$G$2,W8>$G$5),$C$10,$C$9)		RMSE (calibration)
9	=IF(OR(W9<=$G$2,W9>$G$5),VLOOKUP($X9,$A$20:$T$83,18,FALSE),VLOOKUP($X9,$A$20:$T$83,17,FALSE))	=IF(OR(W9<=$G$2,W9>$G$5),$C$10,$C$9)		RMSE (validation)
10	=IF(OR(W10<=$G$2,W10>$G$5),VLOOKUP($X10,$A$20:$T$83,18,FALSE),VLOOKUP($X10,$A$20:$T$83,17,FALSE))	=IF(OR(W10<=$G$2,W10>$G$5),$C$10,$C$9)		Mean model (calibration)
11	=IF(OR(W11<=$G$2,W11>$G$5),VLOOKUP($X11,$A$20:$T$83,18,FALSE),VLOOKUP($X11,$A$20:$T$83,17,FALSE))	=IF(OR(W11<=$G$2,W11>$G$5),$C$10,$C$9)		Mean model (validation)
12	=IF(OR(W12<=$G$2,W12>$G$5),VLOOKUP($X12,$A$20:$T$83,18,FALSE),VLOOKUP($X12,$A$20:$T$83,17,FALSE))	=IF(OR(W12<=$G$2,W12>$G$5),$C$10,$C$9)		
13	=IF(OR(W13<=$G$2,W13>$G$5),VLOOKUP($X13,$A$20:$T$83,18,FALSE),VLOOKUP($X13,$A$20:$T$83,17,FALSE))	=IF(OR(W13<=$G$2,W13>$G$5),$C$10,$C$9)		
14	=IF(OR(W14<=$G$2,W14>$G$5),VLOOKUP($X14,$A$20:$T$83,18,FALSE),VLOOKUP($X14,$A$20:$T$83,17,FALSE))	=IF(OR(W14<=$G$2,W14>$G$5),$C$10,$C$9)		Actual
15	=IF(OR(W15<=$G$2,W15>$G$5),VLOOKUP($X15,$A$20:$T$83,18,FALSE),VLOOKUP($X15,$A$20:$T$83,17,FALSE))	=IF(OR(W15<=$G$2,W15>$G$5),$C$10,$C$9)		
16	=IF(OR(W16<=$G$2,W16>$G$5),VLOOKUP($X16,$A$20:$T$83,18,FALSE),VLOOKUP($X16,$A$20:$T$83,17,FALSE))	=IF(OR(W16<=$G$2,W16>$G$5),$C$10,$C$9)		Model
17	=IF(OR(W17<=$G$2,W17>$G$5),VLOOKUP($X17,$A$20:$T$83,18,FALSE),VLOOKUP($X17,$A$20:$T$83,17,FALSE))	=IF(OR(W17<=$G$2,W17>$G$5),$C$10,$C$9)		Error^2
18	=IF(OR(W18<=$G$2,W18>$G$5),VLOOKUP($X18,$A$20:$T$83,18,FALSE),VLOOKUP($X18,$A$20:$T$83,17,FALSE))	=IF(OR(W18<=$G$2,W18>$G$5),$C$10,$C$9)		RMSE
19	=IF(OR(W19<=$G$2,W19>$G$5),VLOOKUP($X19,$A$20:$T$83,18,FALSE),VLOOKUP($X19,$A$20:$T$83,17,FALSE))	=IF(OR(W19<=$G$2,W19>$G$5),$C$10,$C$9)		Mean model
20	=IF(OR(W20<=$G$2,W20>$G$5),VLOOKUP($X20,$A$20:$T$83,18,FALSE),VLOOKUP($X20,$A$20:$T$83,17,FALSE))	=IF(OR(W20<=$G$2,W20>$G$5),$C$10,$C$9)		
21	=IF(OR(W21<=$G$2,W21>$G$5),VLOOKUP($X21,$A$20:$T$83,18,FALSE),VLOOKUP($X21,$A$20:$T$83,17,FALSE))	=IF(OR(W21<=$G$2,W21>$G$5),$C$10,$C$9)		
22	=IF(OR(W22<=$G$2,W22>$G$5),VLOOKUP($X22,$A$20:$T$83,18,FALSE),VLOOKUP($X22,$A$20:$T$83,17,FALSE))	=IF(OR(W22<=$G$2,W22>$G$5),$C$10,$C$9)		
23	=IF(OR(W23<=$G$2,W23>$G$5),VLOOKUP($X23,$A$20:$T$83,18,FALSE),VLOOKUP($X23,$A$20:$T$83,17,FALSE))	=IF(OR(W23<=$G$2,W23>$G$5),$C$10,$C$9)		
24	=IF(OR(W24<=$G$2,W24>$G$5),VLOOKUP($X24,$A$20:$T$83,18,FALSE),VLOOKUP($X24,$A$20:$T$83,17,FALSE))	=IF(OR(W24<=$G$2,W24>$G$5),$C$10,$C$9)		
25	=IF(OR(W25<=$G$2,W25>$G$5),VLOOKUP($X25,$A$20:$T$83,18,FALSE),VLOOKUP($X25,$A$20:$T$83,17,FALSE))	=IF(OR(W25<=$G$2,W25>$G$5),$C$10,$C$9)		
26	=IF(OR(W26<=$G$2,W26>$G$5),VLOOKUP($X26,$A$20:$T$83,18,FALSE),VLOOKUP($X26,$A$20:$T$83,17,FALSE))	=IF(OR(W26<=$G$2,W26>$G$5),$C$10,$C$9)		
27	=IF(OR(W27<=$G$2,W27>$G$5),VLOOKUP($X27,$A$20:$T$83,18,FALSE),VLOOKUP($X27,$A$20:$T$83,17,FALSE))	=IF(OR(W27<=$G$2,W27>$G$5),$C$10,$C$9)		
28	=IF(OR(W28<=$G$2,W28>$G$5),VLOOKUP($X28,$A$20:$T$83,18,FALSE),VLOOKUP($X28,$A$20:$T$83,17,FALSE))	=IF(OR(W28<=$G$2,W28>$G$5),$C$10,$C$9)		
29	=IF(OR(W29<=$G$2,W29>$G$5),VLOOKUP($X29,$A$20:$T$83,18,FALSE),VLOOKUP($X29,$A$20:$T$83,17,FALSE))	=IF(OR(W29<=$G$2,W29>$G$5),$C$10,$C$9)		
30	=IF(OR(W30<=$G$2,W30>$G$5),VLOOKUP($X30,$A$20:$T$83,18,FALSE),VLOOKUP($X30,$A$20:$T$83,17,FALSE))	=IF(OR(W30<=$G$2,W30>$G$5),$C$10,$C$9)		

Chapra and Canale Model Formulas

	AG	AH
1	**AR TP Data**	
2		
3	35542	35598
4	16	12
5		
6	=VLOOKUP(AG3,$V$3:$AB$3655,4,FALSE)	=VLOOKUP(AH3,$V$3:$AB$3655,4,FALSE)
7	=(AG6-AG4)^2	=(AH6-AH4)^2
8	=SQRT(SUM(AG7:BJ7)/30)	
9	=SQRT(SUM(BJ7:DB7)/45)	
10	=AVERAGE(AG6:BJ6)	
11	=AVERAGE(BK6:DB6)	
12	**AR DO Data**	
13	35535	35542
14	10.7	10.4
15		
16	=VLOOKUP(AG13,'CM Formulas'!$V$3:AD:	=VLOOKUP(AH13,'CM Formulas'!$V$3:AD
17	=(AG16-AG14)^2	=(AH16-AH14)^2
18	=SQRT(SUM(AG17:DC17)/75)	
19	=AVERAGE(AG16:DC16)	
20		
21		
22		
23		
24		
25		
26		
27		
28		
29		
30		

Chapra and Canale Model Formulas

Eutrophication of Reservoirs on the Colorado Front Range

Section IV. Summary of Top-Down vs. Bottom-Up Influences in Reservoirs

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Water quality management in reservoirs has, in the past, been largely the realm of engineers and hydrologists (e.g., Kennedy 2001). However, with the increasing occurrence of persistent eutrophication problems, aquatic biologists have started playing a greater role in determining causal factors of eutrophication and conducting research to identify mitigation strategies. Eutrophication of reservoirs that provide drinking water presents several problems including foul odors, anoxic conditions causing fish kills, and excessive algae blooms that detract from swimming, fishing, and other recreational activities. More importantly, severe eutrophication in reservoirs can pose a significant threat to safe and healthy sources of drinking water for dependent communities. Water quality professionals have traditionally viewed water quality as a result of bottom-up causes (nutrient inputs and availability) while biologists often consider water quality to include top-down factors (food web configurations and trophic cascades). This paper summarizes the routes of control that bottom-up and top-down influences have on water quality, and discusses the relative importance of each as they pertain to reservoir trophic states, especially those reservoirs of the Colorado Front Range that were examined in this study.

Bottom-Up and Top-Down Controls

Bottom-up (nutrient-controlled) influences in aquatic ecosystems (Figure 1) can shape productivity patterns in lentic systems such as lakes and reservoirs. Phosphorus is usually the limiting nutrient in aquatic ecosystems (as opposed to nitrogen in terrestrial systems) and can dictate algal productivity. Often, water quality problems stem not from an overabundance of algae per se, but the wrong kind of algae. For example, increases in phosphorus (from fertilizers, raw sewage, etc.) can lead to blooms in blue-green algae, which are toxic or inedible to zooplankton. The increased abundance of blue-green algae can have effects that are magnified throughout the food web; zooplankton lose a food source, decline, and so do the planktivorous fish that rely on them leaving only algal scums that are often cited in reports of "poor" water quality.

Phosphorus is an essential element in the genetic materials DNA and RNA, as well as necessary for energy storage and transformation in ADP and ATP. However, phosphorus is often scarce in aquatic systems for several reasons (Horne and Goldman 1994). First, most phosphorus is stored in rocks and minerals, but erosion of these materials occurs over large time scales and phosphorus is thus limited in its release to the watershed. Terrestrial plants usually quickly absorb what little phosphorus is released (Schlesinger 1997), and most of the small fraction of phosphorus that enters a lake will be quickly adsorbed onto suspended particles and precipitated to the hypolimnion where it is unavailable to algae. Phosphorus is biologically available only in its soluble form, PO_4. PO_4 can be recycled within the epilimnion by bacteria, phytoplankton, zooplankton, and fish, but becomes unavailable to these organisms if it is transformed into inorganic compounds such as $Ca_3(PO_4)_2$ and $Fe_3(PO_4)_2$ and they precipitate to the hypolimnion. In shallow lakes, internal loading can cause extended eutrophication by releasing phosphate from these compounds under anoxic conditions that occur with high rates of decomposition. However, internal loading is limited in deep lakes because phosphate released through decay and inorganic sediments in the hypolimnion are only infrequently recycled to the epilimnion during rare holomictic mixing events (Horne and Goldman 1994). In cases where phosphorus is very limited, it has been shown that phosphorus-deficient algal cells pass relatively undigested through zooplankton guts, which implies that nutrient-stressed phytoplankton can control zooplankton abundance (van Donk and Hessen 1993).

Because nitrogen is typically available in many aquatic systems, it is usually not a limiting factor for productivity. Nitrate (NO_3^-) moves rapidly through soils and is readily incorporated into ground and surface waters. Nitrate, after undergoing denitrification, can be fixed by bacteria and used by phytoplankton in the form of N_2. However, the most available and directly useable form of nitrogen is ammonia (NH_4^+) that is excreted by zooplankton and fish through their waste products, as well as through mineralization processes that occur in organic detritus (Horne and Goldman 1994). It has been shown that nitrogen is limiting for phytoplankton in some Colorado reservoirs at some times of the year (Lewis and Saunders 2001; Morris and Lewis 1988).

Influences in food webs not only work in the direction from nutrients to higher trophic levels, but also in a "top-down" direction whereby top predators can control the types and abundance of organisms in lower trophic levels (Figure 1; see Northcote (1988) for an excellent review). In this scenario, the number of trophic levels is important in determining relative abundance of each type of organism. For example, in an odd-numbered food chain (three levels: phytoplankton, zooplankton, and planktivorous fishes), planktivores limit the zooplankton population which releases phytoplankton from grazing pressure and allows it to increase in abundance. With even-numbered food chains (piscivorous fish being the top predators), planktivorous fish are controlled by predation so that the zooplankton population is allowed to grow, and subsequently limits phytoplankton abundance. However, in neither case will the food web necessarily collapse due to the lack of phytoplankton or zooplankton. Because of the rapid regeneration times for phytoplankton and zooplankton, the lower trophic levels can still provide adequate food resources for higher trophic levels while not appearing overly abundant in the environment. This inverted trophic pyramid occurs when biomass of lower trophic levels is less than that of higher levels; however, productivity and regeneration are rapid enough to support higher trophic levels. There are exceptions though; mesocosm and whole-lake experiments have shown that presence or absence of fish (or relative predation pressure) can strongly influence zooplankton (and therefore phytoplankton) populations. (Scheffer et al. 2000) found that the control of *Daphnia* over phytoplankton could be altered with a critical fish density, and that this density-threshold increased for systems having higher ambient nutrient concentrations. Critical densities of grazers also exert top-down pressure in the littoral zone of lakes and ponds; low nutrient concentrations can pave the way for strong control of zooplankton and other grazers over phytoplankton biomass (Scheffer 1999).

Elliott et al. (1983) performed experiments that illustrate how top-down pressures can affect water quality and nutrient availability. In simulated epilimnetic communities turbidity and primary productivity (algal biomass) were examined by experimentally manipulating the food web. Treatments included algae alone; algae with zooplankton; and algae, zooplankton, and fish. In treatments with only algae and algae with zooplankton and planktivorous fish, nutrient concentration decreased while algal biomass and detrital concentrations (and therefore turbidity) remained high. In experiments where phytoplankton was controlled by zooplankton (no fish), zooplankton abundance increased along with water clarity. In addition to bottom-up effects, these results show how the trophic cascade (top-down effects) can control water clarity and nutrient availability.

Weighing Top-Down and Bottom-Up Controls

The relative influence of fish on trophic cascades will vary by system. In a study that examined the magnitude of fish control over algal abundance (Persson 1997a), reductions in zooplankton alone did not reduce algal biomass (i.e. when fish zooplanktivory was increased). However, phytoplankton biomass increased when zooplankton populations were decreased and when fish excretions were added to the experimental systems that aided in nutrient regeneration. This suggests that it is not predation alone that creates the difference in algal biomass between even- and odd-numbered food chains, but that fish (and probably other biological) excretions influence phytoplankton abundance as well. Furthermore, Persson (1997b) found that phosphorus excreted by fish (bream and roach) in the form of ammonium phosphate (directly useable to phytoplankton) was on the same order of magnitude as external loading (inputs received from the external environment) and comprised nearly half of the internal loading of phosphorus (which includes inputs from decomposition and sediment release) in eutrophic Finjasjön, Sweden.

Biomanipulation experiments have shown that through human manipulation of fish in food webs, we can alter zooplankton size structure and species composition, and decrease phytoplankton and algal abundance. The Lake Mendota biomanipulation experiment (Lathrop et al. 2002), for example, showed that when planktivores were removed from a system (in this case cisco), the zooplankton population not only greatly increased in number, but the species composition changed from small-bodied cladocerans to larger-bodied ones (Figure 1). Subsequently, nuisance algal blooms were curbed by a dramatic increase in zooplankton abundance. Similarly, if planktivores are released from predation by top predators, zooplankton populations can decrease and primary productivity can increase if left unchecked by grazers.

Determining the degree to which a system is influenced by top-down and bottom-up factors should largely be examined on a case-by-case basis, as all aquatic systems, have different environmental factors controlling the way they function. Lentic systems will vary in their watershed area, nutrient inputs, depth and shoreline development, use (magnitude and type of use), and food web configuration. It is difficult to generalize about trends in trophic state for lentic systems because none are regulated in either a top-down or bottom-up fashion – both components are always present. Dominance of controls can alternate depending on season, climate (i.e. dry vs. wet years), management strategies (such as fish stocking) or with age as nutrient inputs or food webs change. Water management in reservoirs adds even more complexity. Furthermore, the roles of fishes in top-down and bottom-up forces are broadening with more research. For example, Schindler et al. (1993) found that in a system where the highest trophic level consisted of planktivores, most phosphorus available to algae was excreted by fish (see also Schindler et al. (2001)). In addition, fish and other organisms (i.e. *Mysis* and *Chaoborus*) that make diel vertical migrations can provide a significant source of phosphorus to algae by moving it from the hypolimnion into the epilimnion (Schindler et al. 1993; Perez-Fuentetaja et al. 1996; Chipps and Bennett 2000; Schaus and Vanni 2000). Vanni and Layne (1997) and Vanni et al. (1997) provide summaries of the top-down control of planktivorous fishes on zooplankton communities that also contribute to bottom-up effects (Figure 2): first, planktivores decrease average zooplankton size, which results in reduced grazing rates on algae as well as increases recycling rates of phosphorus within the zooplankton community. Second, fish excrete nutrients directly, providing usable phosphorus to algae. It is interactions like these that blur lines between top-down and bottom-up mechanisms in lakes and reservoirs, and which add to confusion about what end of the food web to attack to address water quality problems.

We propose that there are three main areas of concern that can help managers determine what the dominant mechanism of control is in their system of interest. First, some basic physical characteristics can reveal much about the type of lake or reservoir one is dealing with (Kennedy 2001). *Average depth* is important in determining the frequency of turnover events, and therefore, nutrient availability to organisms in the epilimnion as well as possible oxygen limitations in the hypolimnion. *Shoreline development and watershed size* can reveal information about how much phosphorus is entering the system – is the reservoir in a high-elevation watershed that is small, or is it in a major drainage area that collects runoff from a large urban area? *Retention time* is also significant in examining how long nutrients may stay in a system, and where. Differences between reservoir inflow and outflow rates in wet vs. dry years can either sequester or flush out nutrients. Further, the depth of water withdrawal can influence whether incoming water (and nutrients) is skimmed across the surface of the reservoir and released without mixing, or if incoming nutrients have time to be incorporated into the epilimnetic food web and eventually released into the hypolimnion.

Second, the amount of soluble reactive phosphorus in the lake or reservoir is important in helping to determine the potential for lake or reservoir productivity. Again, many if not most aquatic ecosystems are limited by phosphorus, and if nutrients are in high-enough supply to plants they can often mask top-down effects of zooplankton grazers on phytoplankton. While zooplankton can control phytoplankton even with phosphorus loading rates that well exceed those that cause eutrophication (up to 3.19 mg m^{-2} d^{-1}, as in Carpenter et al. (1995)), further increases in phosphorus loading can cause toxic blooms of blue-green algae that are often toxic to or inedible by zooplankton. Scheffer and Rinaldi (2000) report that cyanobacterial colonies can reduce the filtering rates of cladocerans by up to 50% and can not be controlled simply by zooplankton grazing if planktivores are present.

Lastly, it is important to know the food web configuration of the system in question. Are planktivores and/or piscivores stocked in the system? As discussed previously, the presence of planktivores can suppress zooplankton abundance, as well as shape the community towards smaller-bodied zooplankters that recycle N and P at rates differing from larger cladocerans. Both of these changes can result in higher algal abundance and decrease water clarity. The presence of piscivores can release zooplankton from predation by planktivores. There are special cases too – for example, gizzard shad are omnivorous and feed on organic detritus in sediments as well as zooplankton and phytoplankton. Gizzard shad, therefore, can impact phytoplankton directly by both top-down and bottom-up effects (Schaus and Vanni 2000). Carp and other benthivorous fishes can enhance nutrient availability not only by excretion of nitrogen and phosphorus, but also by bioturbation of sediments and resuspending nutrients back into the water column, increasing inorganic turbidity. Fine suspended particles can clog the filtering apparatus of zooplankton and inhibit grazing by *Daphnia* and other zooplankters.

The trophic state of lentic systems depends upon many factors, many of which are ignored, difficult to quantify, or are simply unknown to humans. However, we do have the capabilities to examine physical properties of lakes and reservoirs (e.g., average depth and shoreline development), measure nutrient concentrations, and exert heavy control over food web composition. Biomanipulation projects that have sought to decrease water quality problems have had variable success, but it seems that controlling nutrient inputs and adding piscivores to overly productive systems have been popular methods of controlling algae growth (Lathrop et al. 1996; Horppila et al. 1998; Mehner et al. 2001). Models that seek to predict water quality surely will become more accurate when incorporating nutrient contributions and predation pressures by fish along with typical bottom-up factors. However, it is important that “we should be alert to the imminent danger of an unconscious selection and of a magnifying of phenomena that fall into harmony with the theory and support it and an unconscious neglect of phenomena that fail of coincidence” (Chamberlin 1897). While it is the purpose of models to strike a compromise between detail in the inputs and accuracy in the outputs, water quality managers would be well off to incorporate both bottom-up and top-down controls in deciding upon the most appropriate management decisions for a desired outcome. Figure 3 summarizes the effects that fishery management, water operations, and land use have on the food web and water quality in Front Range reservoirs.

Top-Down and Bottom-Up Factors in Front Range Reservoirs

Assessing the trophic status of lotic water bodies, reservoirs in particular, can be a challenge. The trophic state of lakes and reservoirs is often evaluated by using a trophic status index, which relies on either secchi depth, chlorophyll-a, or soluble reactive phosphorus concentrations, or a combination of these three measurements. However, though we may be able to determine the trophic state of a water body, it does not necessarily mean that we know why it is particularly eutrophic or oligotrophic. For this reason, it is often difficult for managers to try to implement controls on water quality when they don’t know what the source of problems may be.

Several reservoirs along the Front Range are currently facing problematic eutrophication. Because these reservoirs are often used for recreation and drinking water supplies as well as for agriculture, municipalities need to know how to control water quality. Many of these Front

Range reservoirs have exhibited signs of eutrophication such as algal blooms and periodic anoxia in the hypolimnion. Sometimes the expedient solution to such problems is to install an aeration system; however, there might be more effective ways of dealing with over-productive systems simply by taking advantage of top-down controls on productivity.

This is not to say that a lake or reservoir will either be bottom-up or top-down controlled; quite the contrary. In some cases, manipulating food webs can be enough to clear water of excessive phytoplankton, and in others, bottom-up nutrient-driven dynamics will be so strong that top-down controls are masked and have no observable effects on water quality. Certainly, all of our study reservoirs have both top-down and bottom-up processes that are impacting water quality.

Table 1 lists some relevant characteristics of the reservoirs we examined for this study. It is impossible to infer which of these reservoirs may have stronger top-down control over water quality than others, but the wide range of reservoir characteristics and water quality exhibited by the study set suggest possible variation in the value of top down control. Each reservoir will need to be examined further on a case-by-case basis to determine the extent to which top-down forces may be brought to bear on water quality problems, and in situ experiments may be helpful before any management actions are recommended for using top-down controls to improve water quality.

Table 1. Maximum and average depths for each reservoir under study, along with fish species present and water quality comments (made by the municipality in charge of maintaining each reservoir).

Reservoir	Maximum Depth, m	Average Depth, m	Fish	Water Quality
Aurora	110	39	Walleye, Wiper, LM Bass, SM Bass, Yellow Perch, Rainbow Trout, Brown Trout, Channel Catfish, Bluegill, Black Crappie, Spottail Shiner, Stickleback	Good
Rampart	47	- No Data -	- No Data -	High
Quincy	38		LM Bass, SM Bass, Yellow Perch, Black Crappie, Rainbow Trout, Tiger Muskie	Poor - urbanized watershed, anoxic conditions until aeration device installed 1999. Still having blue-green algae problems.
Standley	96	36	Walleye, Wiper, SM Bass, Yellow Perch, Rainbow Trout, White Sucker, Common Carp, Spottail Shiner, Gizzard Shad	Acceptable (anoxic in summer)
Horsetooth	65	- No Data -	Walleye, SM Bass, Rainbow Trout, Carp, White Sucker, Tiger Muskie, Wiper, Brown Trout, Spottail Shiner, Emerald Shiner, Bluegill, Yellow Perch, Gizzard Shad	Fair - Good

Reservoir	Maximum Depth, m	Average Depth, m	Fish	Water Quality
Ralph Price	190	180	Longnose Sucker, Brown Trout, Splake, Rainbow Trout	High
Carter	55	- No Data -	Walleye, LM Bass, Yellow Perch, White Sucker, Kokanee, Splake, Brown Trout, Rainbow Trout, Green Sunfish	Good
Marston	62	26	Walleye, Common Carp, White Sucker, LM Bass	Anoxic in summer, no algae problems.
Burch Lake	36	- No Data -	- No Data -	Low; shallow with abundant plant material
Loveland	- No Data -	8.6	- No Data -	Fair; significant algae blooms anoxia in summer
Boyd	- No Data -	9.1	- No Data -	Fair – Good; some algae blooms and anoxia in summer

Based on the data presented in Table 1, one might conclude that reservoirs of moderate depth that have piscivorous fish and good water quality have strong top-down controls. However, reservoir ecosystems are highly dynamic and without understanding the myriad of other factors that control water quality, including differences in nutrient loading, zooplankton community composition and relative biomasses of piscivores and planktivores, such a conclusion is unwarranted. Most would agree that nutrient loading data would be desirable for all the study reservoirs, but more detailed information on the food webs would also be important for evaluating the prospects for top-down effects on water quality. Food web information, including zooplankton analysis, exist for only two study reservoirs: Horsetooth Reservoir and Carter Lake. In both systems top-down control of the zooplankton was found to be quite strong.

Longterm research at Horsetooth Reservoir (Johnson and Goettl 1999) showed that the fish assemblage was closely linked to the zooplankton. In years when planktivorous fish (rainbow smelt) were abundant, large grazing zooplankton were very extremely rare and the entire zooplankton community was greatly depressed. When the rainbow smelt population declined the zooplankton recovered. The degree to which variation in zooplankton translated into water quality changes was difficult to assess in an observational study since other drivers like water management and nutrient loading were uncontrolled and efforts focused on the upper trophic levels of the food web.

Investigations into the top-down effects of zooplankton on phytoplankton at Horsetooth could be very enlightening since algal blooms and hypoxia in the hypolimnion have created serious water quality problems for the City of Fort Collins. Further, enormous changes in the fish assemblage resulting from the recent drawdown and stocking of forage fish and habitat manipulations by CDOW (have the potential to result in greatly increased zooplanktivory when normal water levels are restored.

At Carter Lake Colorado State University studies showed a strong top-down effect of the planktivorous opossum shrimp (*Mysis relicta*) on zooplankton dynamics (Johnson and Hobgood 2000; Johnson and Graeb 1999). Large zooplankton were nonexistent until mid summer when a thermal refuge from *Mysis* developed in the epilimnion; grazing on algae by zooplankton was likely quite low during spring and early summer. However, Carter Lake managers have not perceived water quality problems there suggesting that nutrient loading (external or internal) is not as severe as at Horsetooth Reservoir.

Eutrophication seems to be more problematic in shallower lakes and reservoirs because nutrients are more available for primary productivity, while in deeper, more stratified water bodies nutrients can be sequestered in the hypolimnion for long periods of time. Recent literature synthesizing years of biomanipulation research, mainly in Europe, suggests that the prospects for enhancing water quality with top-down manipulations of the food web may be best in shallow systems (Mehner et al. 2002; Kasprzak et al. 2002). However, persistent improvements to water clarity in these shallow systems may depend upon a "state shift" involving colonization of the reservoir by rooted aquatic vegetation (Madgwick 1999; Hansson et al. 1998), and such a shift may be undesirable and difficult to achieve in fluctuating reservoirs.

One of the problems with drawing general conclusions about top-down and bottom-up effects is that there are no concrete classifications – there is a gradient of these two controls, including middle-out control and top-down feedbacks on nutrient supply (e.g. fish excretions). City water quality departments collect data in different ways, at different times, and with different measurements. In addition to the data that were collected within this study, it would be helpful to have a measure of phosphorus loading for each reservoir, along with fish population information (for example, is the piscivores population large enough to control planktivores or what is the dominant functional group in fishes present in the reservoir). In-reservoir experiments would be very enlightening regarding the degree to which top-down or bottom-up influences impact lake productivity; for example, measuring chlorophyll-a levels in fish exclosures and enclosures may reveal something about how zooplankton control phytoplankton. Regardless, the reservoirs examined in this study are quite varied in their trophic status, and understanding driving factors of productivity is important for managing water quality. Biomanipulation may be a viable solution for some reservoirs that experience excessive algal production only after the implications of changing lake and reservoir food webs are evaluated and understood.

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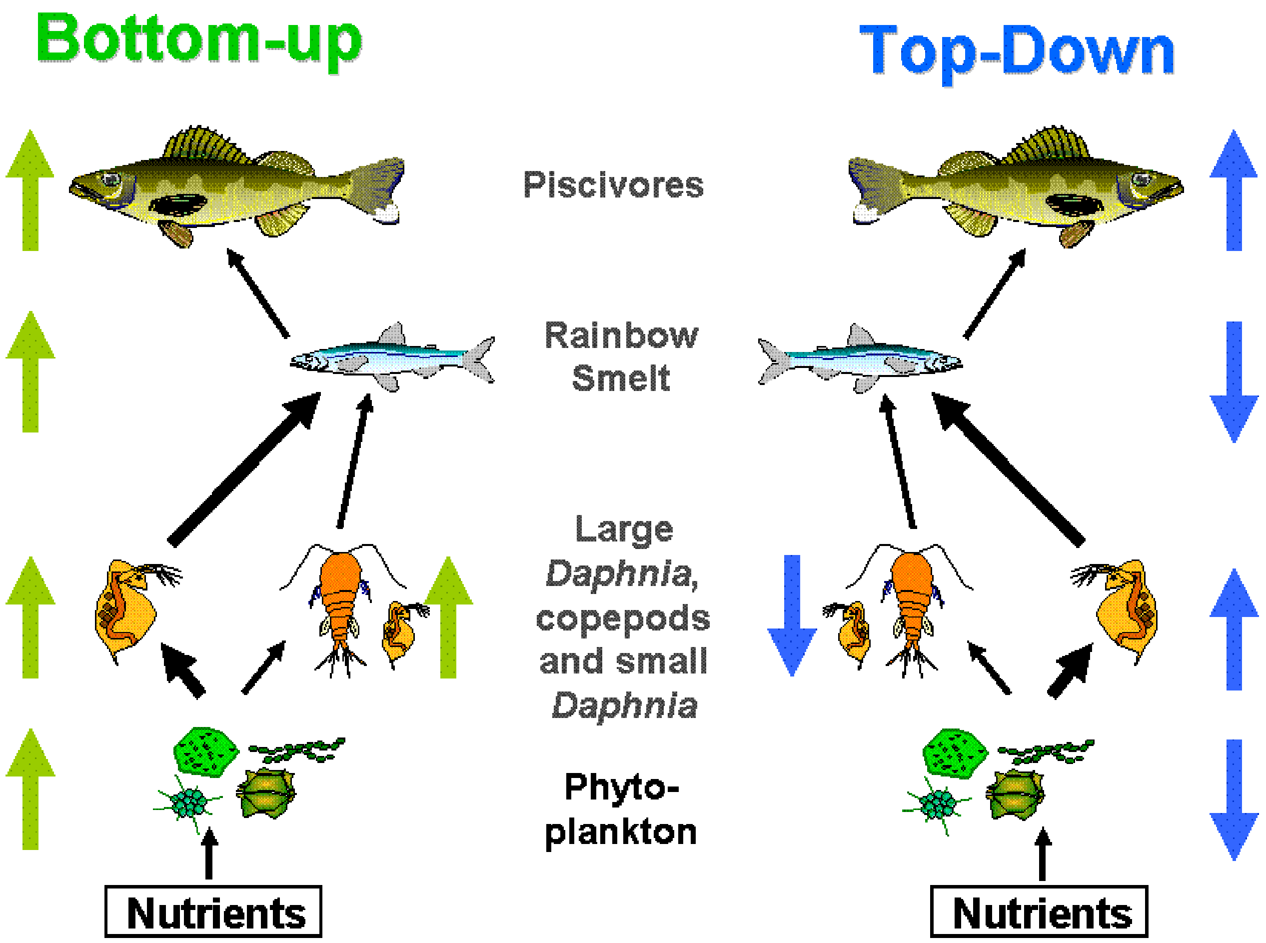

Figure 1. Schematic diagram of bottom-up (nutrient-driven) and top-down (predation-driven) controls on lentic food webs (courtesy of Brett M. Johnson). In the bottom-up route, increases in nutrient supply can lead to increases in overall abundance in algae and zooplankton and support higher trophic levels. In the top-down route, increases in piscivorous fish can suppress planktivore predation on zooplankton, allowing larger zooplankton to proliferate. The opposite can occur when there are no piscivores; planktivores shape the zooplankton community towards smaller-bodied organisms.

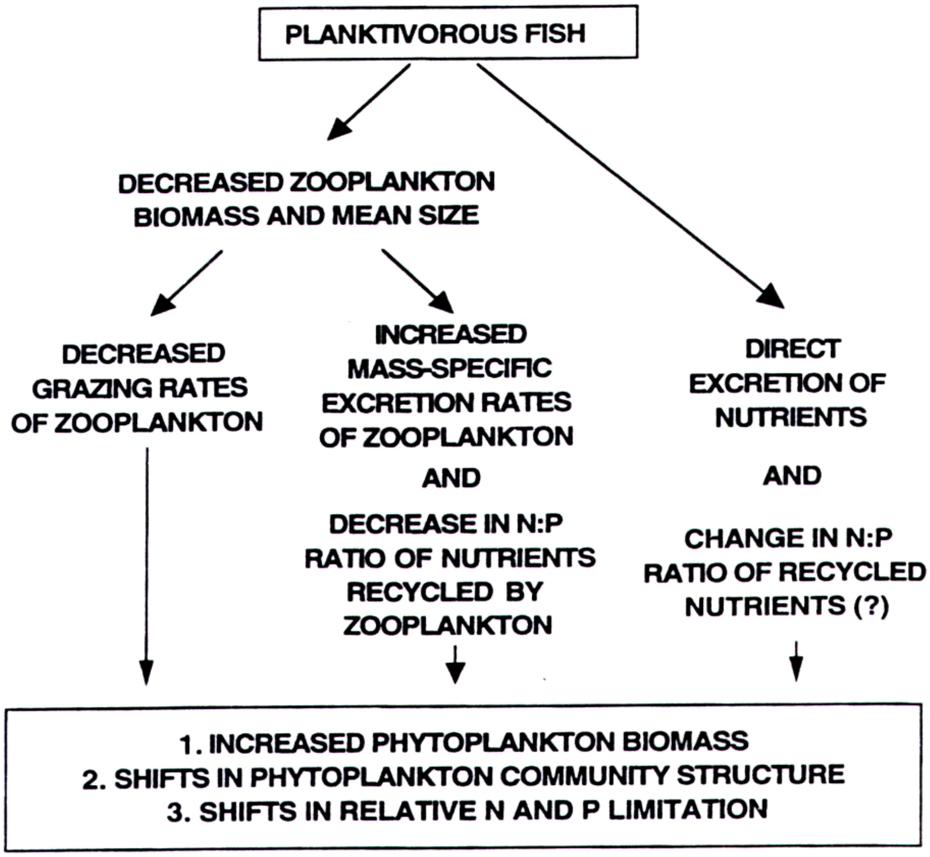

Figure 2. Vanni and Layne (1997) outlined the effects of planktivorous fish on zooplankton and nutrient limitation. Smaller zooplankters have decreased grazing rates on phytoplankton and excrete a higher percentage of phosphorus into the environment. Fish also excrete nutrients directly into the environment as well, illustrating both top-down and bottom-up contributions of phytoplankton by planktivores.

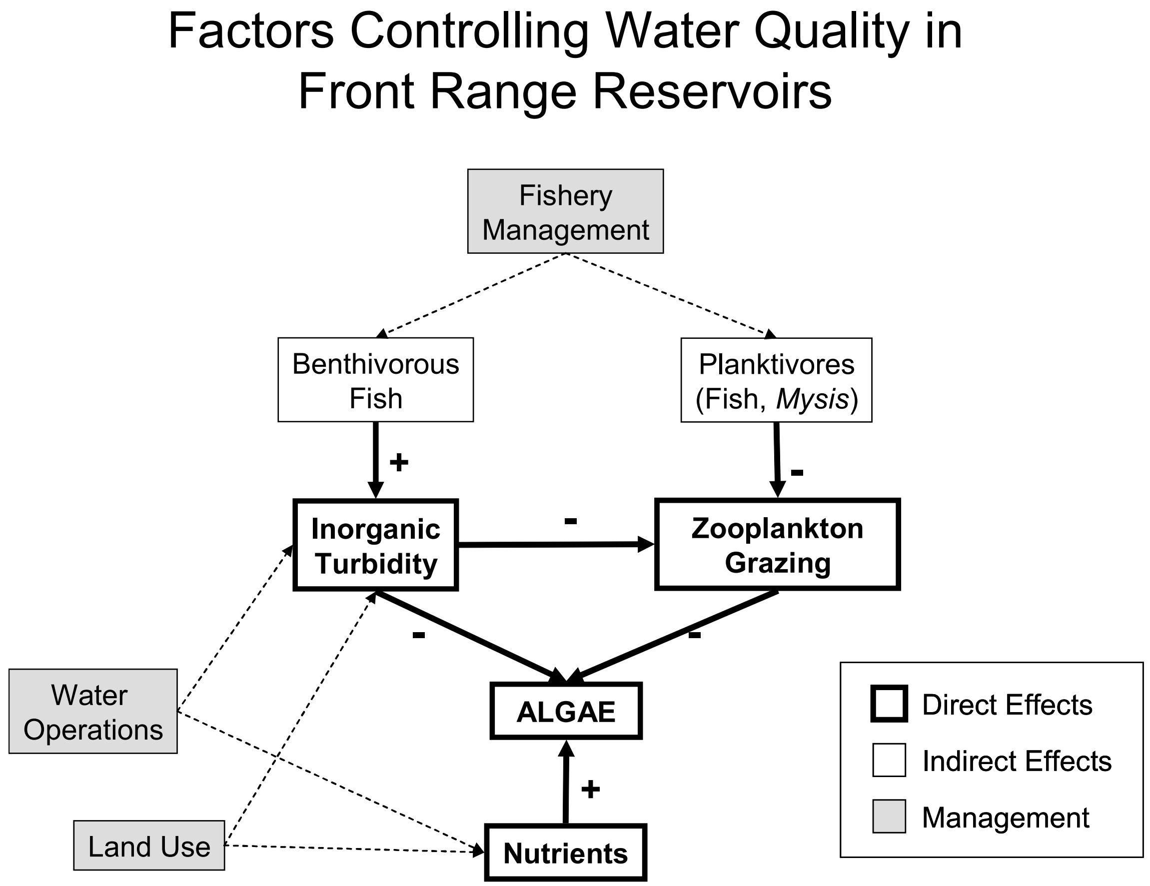

Figure 3. Factors controlling water quality in Front Range reservoirs. Land use and water operations (e.g. seasonal dam operations) impact nutrient loading and inorganic turbidity in reservoirs, while fishery management influences the abundance of fishes such as benthivores and planktivores. Food web configuration and turbidity determine zooplankton grazing rates, which can influence algal production. Turbidity can also impact algal growth by shading phytoplankton cells and inhibiting photosynthesis.