ANALYSIS AND PREDICTION OF WATER TREATMENT COSTS AT THE DV HARRIS PLANT IN THE UMGENI CATCHMENT AREA.

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This paper has two objectives: first, to identify the main contaminants responsible for high treatment costs in the Umgeni catchment area, and second, to predict treatment costs from observed levels of contaminants. A partial adjustment model of treatment costs is estimated for the DV Harris plant, which draws water from Midmar Dam, using ordinary least squares regression and principal component analysis. The model highlights important policy issues and explains 61% of the variation in chemical treatment costs. Environmental contaminants have a marked impact on treatment costs. Treatment costs increase when levels of alkalinity, sodium and turbidity fall. Conversely, costs rise with higher levels of dissolved oxygen and water stability. Paradoxically, clean water - typical of Midmar Dam - is expensive to treat. Treatment costs also rise when concentrations of the algae, Chlorella, decline. Apparently the level of Chlorella varies inversely with the level of other, more harmful, contaminants.

SAMEVATTING: ONTLEDING EN VOORSPELLING VAN WATERBEHANDELINGSKOSTE BY DIE DV HARRIS-AANLEG IN DIE UMGENI OPVANGSGEBIED

Hierdie artikel het twee doelwitte : eerstens om die belangrikste kontaminante wat vir hoë behandelingskoste in die Umgeni opvangsgebied verantwoordelik is te identifiseer en tweedens om behandelingskoste van waargenome kontaminantepeole te voorspel. 'n Parsële aanpassingsmodel van behandelingskoste word vir die DV Harris-aanleg, wat water van die Midmardam onttrek, gepas met die gebruik van gewone kleinste kwadrate regressie en hoofkomponente-analise. Die model beklemtoon belangrike beleidskwessies en verklaar 61% van die variasie in chemiese behandelingskoste. Omgewingskontaminante het 'n belangrike effek op behandelingskoste. Behandelingskoste neem toe met dalings in peile van alkaliniteit, natrium en troebelheid. Aan die ander kant styg koste met hoër peile van opgeloste stuurstof en waterstabiliteit. Dis paradoksikaal dat skoon water - wat tipies in Midmardam aangetref word - duur is om te behandel. Behandelingskoste styg ook met dalende konsentrasies van die Chlorella alge. Die Chlorella peile varieer blykbaar omgekeerd eweredig tot peile van ander, meer skadelike kontaminante.

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1. INTRODUCTION

The enrichment of scarce water resources with plant nutrients such as phosphorus and nitrogen, generally known as eutrophication, creates many problems for development in South Africa (O'Keeffe *et al.*, 1992; Haynes & Viljoen, 1985). The main consequence of eutrophication is abundant algal growth. This study has two objectives: first, to identify the main contaminants responsible for high treatment costs in the Umgeni catchment area, and second, to predict treatment costs from observed levels of contaminants. Treatment costs refer to financial costs incurred in ensuring that the water is potable. In 1995, Umgeni Water spent R 8 046 252 on the purification of drinking water (Umgeni, 1995).

This paper describes a partial adjustment model to analyse treatment costs, and presents results estimated for the DV Harris plant which draws water from Midmar Dam. Similar studies are planned for other treatment plants in the Umgeni valley where poor water quality poses a far more serious problem. Although Midmar Dam is characterised by relatively clean water, it was selected for the initial study in order to test the effectiveness of the techniques used to analyse treatment costs. Umgeni Water is currently developing a model that relates algae levels to various environmental factors. The results of the economic and algae/environment models will be combined to explore links between land use activities, water quality and treatment costs. Reliable information about the origin of high treatment costs is required to inform both policy and planning decisions.

2. THE PROBLEM

Policy-makers can attempt to influence the demand for, or supply of, scarce water resources (Mirrilees *et al.*, 1994). Management involves mechanisms such as quotas, property rights, water markets and other allocative institutions. However, these are beyond the scope of this study. In managing supply, "water authorities and engineers have traditionally tried to alleviate shortage by making more and better resources available" (Mirrilees *et al.*, 1994: appendix A.1-2). In other words, water managers are concerned with both the *quantity* and the *quality* of water as determinants of the available water supply. This study focuses on the quality aspect. If water is of poor quality it may not be readily or realistically available for use, and treatment may be very time consuming or prohibitively expensive.

2.1 Causes of water quality deterioration

Whereas the quantity of water is largely determined stochastically by natural phenomena, the quality of water is greatly influenced by human activities. These are known as *anthropogenic effects* (Breen *et al.*, 1985) and include:

Land use patterns: Changes in farming practices, formal and informal settlements, and industrial growth have an impact on water quality.
Flow management: Water quality in a river is governed by the interaction between nutrient load and river processes. Interruptions to the free flow of a river, either by impoundment or abstraction, affect the quality of its water. Impoundments can affect water quality both positively, by acting as nutrient and sediment traps, and negatively, by causing high concentrations of nutrients. Abstractions too, can increase the nutrient load by reducing the rate of flow (Mirrilees *et al.*, 1994).

Effluent discharge: Increases in effluent discharged from sewage treatment plants and industry can have a detrimental effect on water quality by increasing the load of nutrients and pollutants.

The three main sources of local water pollution as described by Umgeni Water (1995) are:

Industrial waste: Oils, solvents, acids, alkalis and metals.

Agricultural waste: Nutrients from fertiliser run-off, pesticides and suspended solids from soil run-off.

Domestic effluent: Disease-bearing faecal bacteria, nutrients and organic material. For policy purposes, these sources are usually categorised into two classes:

Point source pollution enters the water-way at a particular traceable point, *e.g.* industrial effluent and domestic effluent being released from a sewage treatment plant.

Nonpoint source pollution originates from diffuse sources that are not easily identifiable or distinguishable, *e.g.* nutrients from fertiliser run-off and sewage run-off from informal settlements.

According to Dickens (1996), point and nonpoint sources are equally important in the Umgeni catchment. The main contributors to point source pollution are sewerage works and industrial waste whereas nonpoint pollution is attributed to informal settlements stretching along the banks of the Msunduzi and Mgeni rivers, and to numerous timber, sugarcane and dairy farms found in the area.

2.2. Consequences of water quality deterioration

There are several consequences of water pollution. The first of these is aesthetic, with unsightly litter, oil scums and foam patches resulting from pollution. Second, water becomes stagnant and aquatic life cannot survive in these conditions. The third consequence of poor water quality is the health risk. Water-borne bacteria and viruses detected in the Umgeni catchment include those that cause cholera, typhoid, dysentery and infectious hepatitis (Umgeni, 1995).

Eutrophication is another well-documented result of the human impact upon aquatic ecosystems (Wetzel, 1983). It refers to the process of nutrient enrichment, originating mainly from treated and untreated sewage and agricultural run-off (Umgeni, 1995), and an associated increase in primary nutrient production (O'Keeffe *et al.*, 1992). A symptom of eutrophication is the over-abundant increase in algae, aquatic plants or both (Bruwer, 1979). The following problems have been experienced as a result of eutrophication (Bruwer, 1979; Palmer 1980; Haynes and Viljoen, 1985):

Increased cost of water treatment to potable standards. Costs increase due to increased demand for treatment chemicals and decreased length of filter runs. All the usual treatment chemicals (section 2.3) are used in greater quantities and activated carbon may also be necessary to eliminate taste and odour problems caused by blue-green algae. Filters get clogged with algae and treated water is wasted on frequent backwashing.

The production of anaerobic hypolimnia in lakes. This occurs in warm, deep lakes and when large numbers of algae die at the same time, consuming oxygen in the water as they decompose. This has adverse effects on lake biota - especially oxygen dependent organisms - and lake chemistry.

Aesthetic problems include both the problem of large unsightly algal blooms, and the 'rotten-egg smell' (hydrogen sulfide) which is characteristic of deoxygenated water.

Interference with the recreational use of water bodies. Algal blooms interfere with the recreational use of water bodies and degrade the beauty of the area. Blue-green algae may cause skin irritations and gastro-enteritis in swimmers.

Loss of livestock as a result of algal toxins produced by certain algae.

Fish deaths in saline lakes due to toxin producing algal blooms.

Adverse effects on adjacent real estate development. Property developments next to water bodies may suffer rapid depreciation if the water quality deteriorates causing aesthetic problems; for example the Marina da Gama, in Muizenburg, where unsightly blooms and bad odours became problematic (Bruwer, 1979).

Of concern in this analysis is the fact that water pollution exacerbates eutrophication which leads to increased algal growth and high treatment costs to ensure the provision of potable water. A brief description of the treatment process is relevant at this point as it lends perspective to the models presented in section 4.

2.3. The treatment process at DV Harris

Water extracted from dams and rivers via pipelines and tunnels is passed through wire screens to remove any solid objects. As the water enters the treatment plant a sample of it flows through a series of recording instruments. These measurements determine the appropriate dosage of treatment chemicals. The amount of sediment suspended in the water is a key determinant of its treatment cost because it defines the level of polymer needed to coagulate suspended particles and dirt into floc (Umgeni, 1995). Lime may also be required to adjust the pH to a level at which the polymer works optimally. Bentonite - a type of clay - must be added if the water is 'too clean', *i.e.* if there are too few sediment particles for the floc to form effectively (Graham, 1995). Powdered activated carbon is added when necessary to remove bad tastes and odours caused by algae and other contaminants. Clear water is skimmed off and passed through graded sand filters which remove all remaining suspended matter. Finally, chlorine is added to kill any remaining microbes (Umgeni, 1995). Chlorine is usually applied in gaseous form and may be mixed with ammonia when the water has a long way to travel. Ammonia helps to extend the effectiveness of the chlorine gas (Graham, 1995).

Bentonite improves the efficiency of polymer when the water is 'too clean'. In effect, bentonite is a substitute for polymer. Figure 1 shows that changes in treatment costs at the DV Harris plant follow changes in the combined cost of bentonite (B) and polymer (P). This result was predictable because Midmar Dam is characterised by relatively clean water.

3. DATA SOURCE

Data used in this study were sourced from Umgeni Water. Observations were recorded at regular intervals over a period of six years, 1990 to 1995. Water quality data and dosage rates were supplied by Umgeni's Water Quality Department. Water chemistry and algae data are accredited by the South African Bureau of Standards and ISO 9000. Cost data, measured at 1995 prices, were supplied by their Purchasing Department. Prices relate to the brand of chemicals used most frequently as substitutes involve similar costs per unit of water treated (Graham, 1995). Costs were expressed per megalitre (Ml) of water treated, and refer only to expenditure on chemicals. The cost of backwashing filters was excluded because Umgeni Water does not make short term adjustments to the time spent backwashing. All observations recorded at the Midmar site were expressed in monthly terms to coincide with monthly measures of chemical usage. Unfortunately, chemical dosage data were recorded only from May 1991 to December 1995, reducing the number of valid observations from 71 to 52.

4. METHODOLOGY AND RESULTS

4.1 Variable selection

Descriptive statistics were calculated and checked by Umgeni staff to ensure that the data had been correctly captured. The observations spanned 79 different algae and 51 environmental variables. In order to isolate the contaminants most closely associated with cost, zero-order correlation coefficients were computed and those with significant coefficients were selected for further analysis. The literature was also checked to ensure that algae and other contaminants recognised as being problematic were not omitted (Collingwood, 1980; Palmer, 1980 and Walker, 1983).

Figure 1: Deviations in the total cost of all chemicals and in the cost of Polymer plus Bentonite

The variables selected for analysis are presented in Table 1. Although cost was significantly correlated with biological oxygen demand and sunlight hours, these variables were omitted owing to a large number of missing values. Nitrite, a potential contaminant, was also excluded because there was no variation in the level of nitrite observed at Midmar Dam.

Table 1: Correlation coefficients for important algae and environmental variables

Variable		Units	Correlation with cost
Chlorella	(CHLEL)	cells per ml	-0.4590**
Crucigenia	(CRUCI)	cells per ml	-0.3049*
Gonium	(GONIU)	cells per ml	0.2870*
Alkalinity	(ALKAL)	mg/l $CaCO_3$	-0.5232**
Sodium	(NA)	mg/l	-0.3114**
Percentage Dissolved Oxygen	(PDO)	%	0.4193**
Secchi	(SECC)	m	0.3252**
Stability	(STAB)	$10^{-4}S^{-2}$	0.4482**
Temperature	(TEMP)	^{o} C	0.3864**
Turbidity	(TURB)	NTU	-0.3692**
Pumping	(PUMP)	Ml	0.3537**
Trend Variable	(NUM)	Month	0.1211

Notes: * implies significance at the 5% level of probability
** implies significance at the 1% level of probability

Biological systems are inherently interrelated, as similar species react in similar ways under the same conditions, and all species compete for available nutrients. The dynamic nature of this system means that the relationship between individual algal species and treatment costs cannot easily be predicted.

Alkalinity is expected to have a negative impact on the cost of treating Midmar water. As alkalinity increases so the quantity of lime needed decreases, decreasing the cost of water treatment.

When the level of sodium is low, the level of dissolved charged particles is also low and renders the polymer inefficient. This necessitates the addition of bentonite (Graham, 1996) and explains the inverse relationship between sodium and treatment costs at the DV Harris plant.

Stability is a measure of the stability of the water column. In summer, when the top layer of water is warmer than water at the bottom of the dam, the water stratifies reducing currents and increasing stability. In winter, when the top layer of water cools, temperature gradients weaken and prevailing winds cause convection currents. These currents stir up the sediment from the bottom of the dam. This suggests a negative relationship between stability and treatment costs. However, the effect is reversed when the water is particularly clean because bentonite has to be added for effective treatment. This situation is typical of Midmar Dam and explains the positive correlation between stability and treatment costs.

Turbidity measures the amount of light either absorbed or scattered by particles suspended in the water sample. Consequently, turbidity rises with the level of sediment found in an impoundment. While this would appear to suggest a positive relationship between turbidity and treatment costs, the effect is reversed at DV Harris because water from Midmar Dam is 'too clean' and bentonite has to be added to make the flocculent effective. Secchi reports the depth at which a metal disc lowered into the dam is last visible. It is therefore an inverse measure of suspended solids and is expected to impact positively on the cost of treating water that is 'too clean'.

As anticipated, temperature is positively correlated with treatment costs because it captures seasonal effects. Treatment costs increase in summer when higher levels of runoff add to nutrient loads and pollutants found in the storage dams.

The variable PUMP, which is positively correlated with treatment costs, measures the quantity of water pumped from the Mooi River to Midmar Dam. Past experience has shown that treatment costs rise when pumping occurs, but the exact reasons for this have yet to be established (Freese, 1995). Similarly the causal relationship between percentage dissolved oxygen and treatment costs is not well understood. The trend variable (NUM) measures long-term changes in treatment costs and was retained for analysis in order to isolate the variables responsible for short-term variations in treatment costs.
A distributed lag model has intuitive appeal for analysing water treatment costs because cost incurred in one period is a function of nutrient loads in previous periods. In this case, the distributed lag model can be rationalised as

an autoregressive partial adjustment model (Gujarati, 1988: 515; Kelejian and Oates, 1989) and estimated using ordinary least squares regression (Gujarati, 1988: 519). The partial adjustment model postulates that actual treatments are intended to satisfy minimum rather than optimum standards of water quality. Consequently, the desired or optimum level of treatment and its associated cost Y* is unobservable:

$$Y_t^* = b_o + b_1X_t + U_t \tag{1}$$

Where

X_t represents the level of one explanatory variable in time period *t*.

Nerlove (cited by Gujarati, 1988: 520) expresses the partial adjustment model as follows:

$$Y_t - Y_{t-1} = d(Y_t^* - Y_{t-1}) \tag{2}$$

where d, such that 0<d<1, is known as the *coefficient of adjustment*, where $Y_t - Y_{t-1}$ is the actual change, and $Y_t^* - Y_{t-1}$ the desired change. If d = 1, it means that actual cost is equal to the optimum cost, *i.e.* actual cost adjusts to the optimum level in the same time period. If d = 0, it means that nothing changes since the actual cost at time *t* is the same as that observed in the previous time period. Typically, d is expected to lie between these extremes because treatments are aimed at meeting minimum rather than optimum standards of water quality.

Rearranging the terms in equation (1) and substituting into equation (2) yields the partial adjustment model in its estimable form:

$$Y_t = dbo + db_1X_t + (1 - d)Y_{t-1} + dU_t$$

4.2 Results

Results of the model estimated for the DV Harris plant are presented in Table 2. Explanatory power is reasonably good (R^2=64%) but the *t*-values are extremely low. This is a classic symptom of the multicollinearity anticipated in the model (Gujurati, 1988: 299). The variable LCOST represents treatment costs lagged by one period. In terms of the partial adjustment model, the coefficient estimated for this variable represents the share of the optimum level of treatment which is not achieved during the current period.

Principal component analysis was employed to overcome the problem of multicollinearity (Chattterjee & Price, 1977). This technique converts the original variables into uncorrelated variables called principal components, PC's, which are linear combinations of the original variables:

$$PC_i = a_{i1}X_1 + a_{i2}X_2 + \ldots + a_{ik}X_k$$

where

PC_i = *i*th principal component
a_{ij} = component loadings[3]
X_j = original explanatory variables

Table 2: Regression coefficients estimated for contaminants before removing multicollinearity

Explanatory Variables	Coefficients (b_i)	*t*-values
Constant	23.053758	2.29**
CHLEL	-0.003275	-1.39
CRUCI	-0.001291	-0.67
GONIU	-0.007458	-0.25
ALKAL	-0.381269	-1.51
NA	-0.456056	-0.42
PDO	0.029775	0.53
SECC	0.470827	0.52
STAB	0.146322	0.55
TEMP	0.033538	0.23
TURB	0.069904	0.59
PUMP	0.001924	0.24
NUM	-0.004266	-0.18
LCOST	0.428797	2.57**
R^2 (%)	64.06	
F	5.07**	

Notes: * implies significance at the 5% level of probability
** implies significance at the 1% level of probability

The principal components must satisfy two conditions; they must be orthogonal and the first component (PC_1) should account for the maximum

[3] PSS normalises factor loadings such that the squared loadings sum to the eigen value. The factor loadings were manually adjusted to that the squared loadings summed to unity.

proportion of variation in the original variables and each subsequent PC should account for the maximum remaining variation in the original variables.

The regression models were then re-estimated using the principal components as explanatory variables and standardised COST (ZCOST) as the dependent variable. No attempt was made to interpret the principal components. They were employed only to combat multicollinearity so that the separate or partial contribution of each contaminant (to treatment costs) could be identified for policy purposes. To accomplish this goal, the models presented in Table 3 were expressed in terms of the original variables following the procedure described by Chatterjee and Price (1977) and Nieuwoudt (1972).

Table 3: Regression coefficients estimated for principal components

Explanatory Variables	Coefficients (a_i)	*t*-values
Constant	0.000025	0.00
PC1	0.366849	7.73**
PC2	-0.166153	-2.45**
PC3	0.003146	0.04
PC4	-0.162119	-1.87
PC5	-0.017304	-0.18
PC6	-0.089502	-0.84
PC7	-0.065376	-0.53
R^2	61.16	

Notes: * implies significance at the 5% level of probability
** implies significance at the 1% level of probability

This procedure uses the component loadings to transform the regression coefficients estimated for the principal components into standardised estimates (b_i) for the original variables. Successive principal components were dropped until the sign and magnitude computed for each estimated coefficient stabilised. Following this approach, seven principal components were retained, accounting for almost 90 per cent of the variation in the original variables.

Table 4 presents the standardised regression coefficients computed for the original explanatory variables. The *t*-values were computed as

$$\frac{b_i}{\sqrt{\mathrm{Var}\,(b_i)}}$$

where

$$\mathrm{Var}(b_i) = \sum_{i=1}^{k} ((\text{PC loading}_i)^2 * \mathrm{Var}(\alpha_i))$$

where

k = the number of principal components retained.

Table 4: Standardised regression coefficients estimated for contaminants after removing multicollinearity

Explanatory Variables	Coefficients (b_i)	*t* -values
CHLEL	-0.16847	-4.16**
CRUCI	-0.12149	-1.25
GONIU	0.09440	0.98
ALKAL	-0.23122	-3.82**
NA	-0.12236	-2.34*
PDO	0.14089	2.37*
SECC	0.02910	0.73
STAB	0.12893	2.58*
TEMP	0.02739	0.59
TURB	-0.07056	-1.60
PUMP	0.01914	0.22
NUM	0.04146	0.47
LCOST	0.18820	4.29**
R^2	61.16	

Notes: * implies significance at the 5% level of probability
** implies significance at the 1% level of probability

These standardised coefficients (b_i) are useful for policy purposes because they are independent of the original units of measurement and therefore show the relative importance of each explanatory variable to changes in cost (Nieuwoudt, 1972). However, for predictive purposes the standardised variables were converted to original scale using the method proposed by Kendall (1957). The b_i's were multiplied by Sy/Sx_i (the standard deviation of the dependent variable divided by the standard deviation of the independent variable) and the constant term was calculated as the difference between the mean values of observed and predicted costs. Table 5 presents the regression coefficients computed for the original variables measured in their original units.

The Durbin *h* statistic computed for the final (corrected) model did not provide a conclusive test for the absence of autocorrelation. However, the Geary Runs statistic fell within its 95 per cent confidence limits so autocorrelation was not considered to be a significant problem (Gujurati, 1995: 420).

Although the final model presented in Table 5 exhibits some loss in explanatory power when compared to the original model, it is clear that the original model was severely affected by multicollinearity. In particular, the *t*-

values created the false impression that none of the contaminants had any significant effect on treatment costs.

Despite the loss in predictive power, the final model was considered to be a more robust predictor of treatment costs owing to the absence of multicollinearity. Figure 2 shows a reasonable match between actual and predicted costs.

Table 5: Unstandardized regression coefficients estimated for contaminants before and after removing multicollinearity

Explanatory Variables	Original Model	*t* -values	Final Model	*t* -values
Constant	23.053758	2.29**	32.15031	
CHLEL	-0.003275	-1.39	**-0.00261**	-4.16**
CRUCI	-0.001291	-0.67	-0.00209	-1.24
GONIU	-0.007458	-0.25	0.02415	0.98
ALKAL	-0.381269	-1.51	**-0.44077**	-3.82**
NA	-0.456056	-0.42	**-0.94854**	-2.34*
PDO	0.029775	0.53	**0.04711**	2.37*
SECC	0.470827	0.52	0.12156	0.73
STAB	0.146322	0.55	**0.14393**	2.58*
TEMP	0.033538	0.23	0.01915	0.59
TURB	0.069904	0.59	-0.03552	-1.60
PUMP	0.001924	0.24	0.00106	0.22
NUM	-0.004266	-0.18	0.00752	0.47
LCOST	0.428797	2.57**	0.19772	4.29**
R^2 (%)	64.06		61.16	
Durbin *h*	-		2.16	

Notes: * implies significance at the 5% level of probability
** implies significance at the 1% level of probability

Figure 2: Predicted versus actual treatment costs at the DV Harris Plant (Constant 1995 prices)

5. DISCUSSION

The results suggest that real treatment costs at the DV Harris plant diminish with an increase in the quantity of *Chlorella* in Midmar Dam (Figure 3). It would seem that the quantity of *Chlorella* varies inversely with the quantity of one or more substitutes, and that the (unobserved) substitutes may pose a serious management problem. (For example, *Chlorella* may be consuming contaminants that would otherwise contribute to an increase in treatment costs.) More research is needed to unmask the harmful substitutes that vary inversely with *Chlorella.*

Figure 4 illustrates the negative relationship between alkalinity and treatment costs at DV Harris. Surprisingly, alkalinity is not significantly correlated with the cost of lime but is correlated with the cost of polymer and bentonite. The cause of this relationship is not obvious and requires further investigation.

Figure 3: Treatment costs versus *Chlorella*

Figure 4: Treatment costs versus Alkalinity

Treatment costs rise with increasing stability (Figure 5) and decreasing turbidity. These relationships and the negative effect of increased sodium levels on treatment costs highlight the paradox of treating water that is 'too clean'.

Figure 5: Treatment costs versus stability

Percentage dissolved oxygen bears positively on treatment costs at DV Harris plant, as seen in Figure 6. The reasons for this positive relationship are unclear and require further investigation by water treatment experts. Lagged cost has no policy implications. Its coefficient suggests that 80 per cent (*i.e.* 1 - 0,1997) of the "full" cost required to achieve optimal (rather than minimal) water quality is incurred in the space of one month.

Figure 6: Treatment costs versus percentage dissolved Oxygen

6. CONCLUSION

The study identifies some important factors contributing to high treatment costs at the DV Harris plant. Environmental contaminants have a marked impact on treatment costs. Treatment costs increase when levels of alkalinity, sodium and turbidity fall. Conversely, costs rise with higher levels of dissolved oxygen and water stability. Paradoxically, clean water - typical of Midmar Dam - is expensive to treat. Treatment costs also rise when concentrations of the algae, *Chlorella,* decline. Apparently the level of *Chlorella* varies inversely with the level of other, more harmful, contaminants. This result, and other relationships identified by the model, highlight several policy issues which require further investigation. Interaction effects were not considered in the study and may also warrant further research.

The estimated model explains 61% of the variation in chemical treatment costs and predicts actual costs well (except during occasional peak cost periods). It could be used as a management tool to simulate savings in treatment costs achieved by altering the level of individual contaminants. Of course, regular updating with current data will be necessary to ensure that the results remain relevant.

NOTES:

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