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COUNTY OF INYO WATER DEPARTMENT

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Development of Multiple Linear Regression Models for Prediction of Water Table Fluctuations

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Introduction.

Despite the ongoing development of numerical modeling tools, multiple linear regression models (MLRM) remain the most reliable and relied-upon tool for prediction of water table fluctuations in the operational implementation of the County of Inyo/City of Los Angeles Long Term Groundwater Management Plan. The County made extensive use of the MLRM during the recent disputes over the operation of the McNally canals and the Annual Operations Plan for 2001-2002, and will likely continue rely on them in the future; therefore, it is desirable to update, reevaluate, extend, and improve the MLRM.

The theory and development of the MLRM is described in Harrington (1998; 1999) and references therein. The general strategy of the MLRM is to use regional groundwater pumping and runoff as driving variables to predict fluctuations in the water table elevation. One of the primary questions regarding the MLRM is: what are the appropriate driving variables to use in the model? Pumping and runoff must be spatially and temporally averaged prior to being input into the model, and the optimum choice of averaging scale is not obvious at the outset of model development. For example, the first regression MLRM scheme applied to Owens Valley groundwater pumping utilized valley-wide pumping as a driving variable (Williams, 1978), whereas the current MLRM use wellfield pumping. In general, the more localized the input variables are, the greater the effort required to assemble the data and implement the model; therefore the optimum scale for averaging the input variable up so that each MLRM used runoff in a few specific streams near the indicator well would require considerably greater data assembly effort for little or no additional model performance, because of the very high correlation between flow in any single stream and Owens Valley runoff as a whole. Conversely, the MLRM can be

expected to perform better if there is a real and direct hydrological linkage between the indicator well and the driving variables. Clearly, if spatial averaging scales are too large, processes contributing to the averaged driving variable do not affect fluctuations in the indicator well.

The objectives of this report are to explore alternative renditions of the driving variables in the MLRM, develop additional indicator wells to extend the spatial coverage of the set of indicator wells, and explore alternatives for assessing the accuracy of the MLRM. This report documents several recent efforts the County Water Department has made to improve and extend the MLRM. These efforts specifically are:

- 1. Use of inflows into the McNally canals as a predictor variable in Laws area MLRM.
- 2. Implementation and comparison of various methods of assessing uncertainty in MLRM predictions.
- 3. Investigation of methods for generating autocorrelated lognormal time series that reproduce the statistics of Owens Valley runoff for use in multi-year MLRM simulations.
- 4. Development of MLRM for wells useful for predicting water table fluctuations at permanent vegetation monitoring sites.

Each of these efforts is somewhat independent of the others, therefore each is described in a separate section.

Use of inflows into McNally canals as a predictor variable in Laws models.

Owens Valley runoff has been used as a predictor variable in the MLRM because it correlates well with recharge from stream channels and surface water conveyances, direct recharge from precipitation, artificial recharge operations, and ungaged mountain front recharge. Owens Valley runoff is more easily measured than recharge, so it serves as a spatially lumped variable that captures the deviation from normal that can be expected in recharge for a given year. The Laws wellfield is an exception to this reasoning because of its location east of the Owens River at the foot of the White Mountains. Other LADWP wellfields in the Owens Valley lie on or at the toe of alluvial fans issuing from the Sierra Nevada, and most recharge to those wellfields comes from snowmelt runoff recharging through stream channels or on the range-front slopes. In contrast, Laws lies on the other side of valley from the snowmelt recharge sources from the Sierra Nevada, and due to the rain shadow of the Sierra Nevada, the White Mountains receive a small fraction of the seasonal snow fall that the Sierra Nevada receives. Therefore, the natural recharge mechanisms that act in other LADWP wellfields are not as effective in the Laws area. The comparatively low amount of natural recharge on the east side of the valley is documented in the Green Book, Appendix B, Tables 1, 3, 4, and 5. The primary sources of recharge for the Laws wellfield are seepage losses from the canal system, percolating irrigation, and artificial recharge due to water spreading activities conducted by LADWP, rather than through natural recharge (Jorat, 2001). Thus motivated, the work presented here sought to determine whether there is another variable than Owens Valley runoff that could be used to better represent recharge in the Laws area.

The largest water conveyances in the Laws area are the Upper and Lower McNally canals, which are used to supply water from the Owens River to spreading areas and irrigated land in the Laws, and to

convey pumped water from production wells to irrigated land and mitigation projects. The canals undergo substantial channel losses when operated, and their operation is often associated with other recharge generating activities (Green Book, 1990; Danskin, 1998); therefore, their flows are likely to be well correlated to recharge and water table fluctuations in the Laws area.

The data used to develop MLRM for the Laws area using the McNally canals are given in Appendix 1. Diversions into the McNally canals from the Owens River are correlated to Owens Valley runoff due to LADWP's historical operational tendency to use of the canals for conveying surface water to Laws area irrigation leases and water spreading basins during non-drought conditions (Figure 1). From a statistical point of view, it is clear that use of either Owens Valley runoff or diversions into the McNally canals as driving variables in MLRM would produce viable models; however, two considerations suggest that diversions into the McNally canals are preferable to Owens Valley runoff. First, as discussed above, the McNally canals have a more direct physical relationship to Laws area recharge mechanisms than Owens Valley runoff. Second, if the relationship between runoff and canal diversions depicted in Figure 1 should change (e.g., if LADWP were to decide to diminish its use of the canals regardless of runoff conditions), then the correlation between Owens Valley runoff and Laws area recharge would no longer be as it has been in the past, rendering the MLRM invalid. In the event that operational management of the McNally canals should change, it is desirable that the driving variables used in the MLRM be causally related to processes effecting water table fluctuations.



Figure 1. Owens Valley percent of normal runoff plotted against diversions into the McNally canals from the Owens River.

Table 1 compares the statistics for regressions performed using Owens Valley runoff and diversions from the Owens River into the McNally canals for each Laws area indicator well. Appendix 1 contains the data. In every case, the coefficient of determination is higher and the standard error lower when diversions into the canals is used as the driving variable, which indicates that the MLRM have more predictive power when implemented with canal diversions as the driving variable related to recharge. Table 1 reveals a modest, but consistent, improvement in the regression statistics when canal diversions are used. If management decisions were to further diminish the correlation between runoff and canal operations, the improvement in modeling capability obtained through use of canal diversions will likely be greater than that shown in Table 1. Regression coefficients for the MLRM based on McNally canal diversions are given in Table 2.

Table 1. Comparison of regression statistics (\mathbb{R}^2 , coefficient of determination; SE, standard error of the
regression) for Laws wellfield MLRM using Owens Valley runoff and diversions from the Owens River
into the McNally canals.

	_	Owens Valley runoff		diversions into	McNally canals
Well	Ν	R^2	SE	\mathbb{R}^2	SE
107T	17	0.894	2.419	0.942	1.786
436T	22	0.880	1.454	0.946	0.972
438T	25	0.799	1.951	0.880	1.508
490T	25	0.890	1.216	0.936	0.928
492T	20	0.901	3.417	0.938	2.693
493T	24	0.896	4.243	0.949	2.964

Table 2. Regression coefficients for MLRM for Laws area wells using diversions from Owens River into the McNally canals as driving variable (Appendix 1).

WellInterceptInitial water levelLaws pumpingRiver into McNally canals107T1940.70.5299-0.00033470.00024434436T1813.30.55730.00013080.00014643					Diversions from Owens
107T 1940.7 0.5299 -0.0003347 0.00024434 436T 1813.3 0.5573 0.0001308 0.00014643	Well	Intercept	Initial water level	Laws pumping	River into McNally canals
<i>426</i> T 1812.2 0.5573 0.0001208 0.00014642	107T	1940.7	0.5299	-0.0003347	0.00024434
4501 1615.5 0.5575 -0.0001508 0.00014045	436T	1813.3	0.5573	-0.0001308	0.00014643
438T 1929.0 0.5327 -0.0001166 0.00014452	438T	1929.0	0.5327	-0.0001166	0.00014452
490T 1065.0 0.7377 -0.0000505 0.00012906	490T	1065.0	0.7377	-0.0000505	0.00012906
492T 2045.1 0.5010 -0.0005186 0.00027338	492T	2045.1	0.5010	-0.0005186	0.00027338
493T 1505.5 0.6334 -0.0003439 0.00041436	493T	1505.5	0.6334	-0.0003439	0.00041436

Implementation and comparison of various methods of assessing uncertainty in the MLRM predictions.

Analytical methods exist for assessing the uncertainty of MLRM predictions, but the validity of these methods requires that the data and residuals generated by the model fully meet the assumptions underlying MLRM (Kufs, 1992). In practice, adherence to the assumptions is never perfect; therefore, it is desirable to compare alternative methods of assessing uncertainty in the MLRM predictions to the classical analytical method. Two uncertainty intervals were examined: the "confidence interval" which is the interval within which the mean value (i.e. regression line, or, in more than two dimensions, the regression hyperplane) of the dependent variable falls, and the "prediction interval" which is the interval within which a single prediction of the dependent variable falls. The uncertainty encapsulated by the confidence interval is related to both the regression coefficients; the uncertainty encapsulated by the prediction interval is related to both the regression coefficients and the tendency for data to not lie

exactly on the regression hyperplane. If the regression coefficients were known exactly, the confidence interval would be zero, but the prediction interval would still be non-zero unless all the data lay exactly on the regression hyperplane. The tendency for the data to not lie exactly on the regression hyperplane is due to both measurement error and the fact that the model only approximates the actual hydrologic system. Harrington (1998) presented a method of using bootstrap resampling and Monte Carlo simulation to evaluate uncertainty in MLRM predictions. Here, three methods of evaluating the uncertainty in MLRM predictions are compared; one method is the classical analytical method (Holder, 1985), the other two are based on bootstrap resampling (Draper and Smith, 1988).

The analytical prediction interval is given by

$$\hat{h} \pm t(n-4,1-\alpha/2)(\hat{\sigma}^2(1+x(X'X)^{-1}x'))^{1/2}$$

where \hat{h} is the water level predicted by the regression, $t(n-4,1-\alpha/2)$ is the *t* statistic for *n*-4 degrees of freedom at $1-\alpha/2$ significance, *n* is the number of data, α is the confidence level of the prediction interval, $\hat{\sigma}^2$ is the variance of the regression residuals, *x* is the data for the estimate, and *X* is the matrix of observations given by

$$\begin{bmatrix} h_1 & p_1 & r_1 \\ h_2 & p_2 & r_2 \\ \vdots & \vdots & \vdots \\ h_n & p_n & r_n \end{bmatrix}$$

where h_i , p_i , and r_i are the initial water table elevation, wellfield pumping, and Owens Valley runoff for year *i*. As discussed above, diversions into the McNally canals are substituted for runoff in Laws wellfield MLRM.

Bootstrap prediction intervals are generated by random resampling and repeated calculation of the regression model based on the resampled data. The first method, bootstrapping the residuals, is implemented by computing the regression model from the original data set, and then resampling with replacement the resulting residuals. The resampled residuals are then added to values predicted by the model and the model coefficients are recalculated. Repeating this process generates as many "realizations" of the model as desired, and the statistics of the set of realizations characterizes the confidence interval. The prediction interval then is derived by adding a normally distributed random number with zero mean and standard deviation equal to the standard error of the regression to each realization.

The second method of bootstrapping, bootstrapping the data, is carried out by resampling the predictor variables from the original data set to form new simulated data sets, and recomputing the regression coefficients from the new data sets. Again, the statistics of the set of realizations characterizes the confidence interval, and the prediction interval is derived by adding a normally distributed random number with zero mean and standard deviation equal to the standard error of the regression to each realization.

To compare the three methods of deriving prediction intervals, the three methods described above were applied to two representative indicator wells, well 493T (Laws wellfield, 24 years of data) and well 418T

(Taboose Aberdeen wellfield, 27 years of data). Well 493T responds rapidly to pumping stress and recharge from the McNally canals, and fluctuations in its hydrograph range over span of forty feet. Well 418T fluctuates over a smaller range, about thirteen feet, and has a smoother hydrograph than well 493T. For each well, the three methods of computing prediction intervals were implemented and applied to the regression data set, generating a prediction interval for the modeled value for each year of the period of record. The bootstrap methods were applied using five thousand realizations. Table 3 lists the mean and standard deviation of the prediction intervals for each method and each well. Also given is the confidence interval calculated by the analytic method.

It can be concluded from Table 3 that all three methods produce similar prediction intervals, suggesting that the indicator well regression data meets the assumptions of linear regression sufficiently to use the analytic method to compute prediction and confidence intervals. For both wells, the analytic prediction interval was slightly greater than either of the bootstrap methods, the greatest difference being between the analytic method and the bootstrap residual method for well 493T of about 6%. These are encouraging results, in that all these methods produce similar enough prediction intervals that any one of them is sufficient to compute uncertainty estimates for MLRM predictions.

The confidence interval for the analytic method is about one-third of the prediction interval, which shows that the greater share of uncertainty in model predictions is due to scatter about the regression hyperplane, not due to uncertain or unstable regression coefficients. It is not surprising, then, that the three methods produce similar uncertainty estimates, because the largest part of the prediction uncertainty is embodied in the standard error of the regression, which makes a similar contribution to the prediction interval in each of the three methods.

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		Prediction intervals		Confidence interval
Well	Analytic	Bootstrap residuals	Bootstrap data	Analytic
493T	6.554(0.206)	6.193(0.208)	6.400(0.313)	2.111(0.579)
418T	1.313(0.028)	1.264(0.035)	1.263(0.058)	0.406(0.088)

Table 3. Mean and standard deviation of uncertainty intervals derived by analytic methods, bootstrapping residuals, and bootstrapping data. Standard deviation in parentheses.

Investigation of methods for generating autocorrelated lognormal time series.

In order to predict water table fluctuations over time intervals of several years, it is necessary to provide the MLRM with groundwater pumping and Owens Valley runoff for the duration of the modeled time interval. Pumping is a variable that is controlled by management decisions. Therefore, it is most appropriately supplied to the MLRM deterministically, and is thus specified exactly in a given simulation. Owens Valley runoff, however, is unknown and varies stochastically. To provide the MLRM with realistic renditions of runoff for multiple years, it is desirable simulate Owens Valley runoff for the period of the simulation in a way that reproduces the important statistics of the historical runoff time series. For this application, the important statistics are the mean, standard deviation, skewness, and one-lag coefficient of autocorrelation. Seasonality of runoff can be neglected, because the MLRM are implemented with one-year time steps, and decadal-scale periodicities are beyond the concern of the one to four year simulations contemplated here. Owens Valley runoff for each runoff year 1935 through 1999 were used to calculate the statistics of the runoff time series (Appendix 2). Figure 2 shows the histogram and Figure 3 shows the normal probability plot of the Owens Valley runoff data set. Table 4 gives the summary statistics for the runoff data set.

Table 4. Summary statistics for the Owens Valley runoff data set.					
Mean	426205 AF				
Standard deviation	155403 AF				
Median	393362 AF				
Skewness	0.7775				
One-lag autocorrelation coefficient	0.1416				



Figure 2. Histogram of Owens Valley runoff.



Figure 3. Probability plot of Owens Valley runoff.

It is clear from Table 4 and Figures 2 and 3 that the distribution of Owens Valley runoff is skewed to the right and should be treated as a non-normal distribution. Typically, runoff time-series can be modeled as lognormally distributed (Haan, 1977), and that appears to be a valid strategy for these data.

Runoff data also typically serially correlated due to climatological and watershed processes that cause the previous years' precipitation conditions to contribute to any given year's runoff. For example, remnant snowfields and moist soil following a year of high precipitation may cause the following year to have more runoff than would be expected based on precipitation alone, or climatological teleconnections such as the El Nino/Southern Oscillation may persist for more than one year. Figure 4 shows a correlogram for Owens Valley runoff. A correlogram is calculated by computing the correlation coefficient between a data set and the same data set off-set by one, two, three, etc. years, e.g., the correlogram at lag = 10 is the correlation coefficient for runoff separated by ten years. The most pertinent feature of Figure 4 for regression modeling is how rapidly the correlogram declines in the first few years. The correlogram for lag = 1 is 0.1416; for lag = 2, it is 0.2106; and for lag = 3, it is -0.0071, suggesting that the degree of serial correlation in the runoff time series is modest. To further evaluate the importance of serial correlation, simple linear regression of the runoff data versus the same data offset by one year was performed. The slope of the regression line was significant at a p = 0.2643 level (for normally distributed data with a one lag autocorrelation coefficient equal to zero, there is probability p that the slope would be this great or greater). This suggests that autocorrelation of the runoff data is not a critical concern, but may be present; therefore, a method is presented here for generating autocorrelated time series of lognormally distributed runoff data. The apparent periodicity in the correlogram suggests some sort of cyclical climatological process with a period of twelve to fifteen years. The MLRM are applied to forecast windows of up to five years, so the observed periodicity does not affect this application.



Figure 4. Correlogram for Owens Valley runoff.

To generate autocorrelated time series of runoff, it is assumed that the statistics of the time series are stationary. This assumption is necessary to estimate population parameters from the data set sample statistics, however it should be recognized that alterations such as land use change, changes in water management, or climate change could render this assumption invalid. The simplest model for simulating Owens Valley runoff that fulfills the requirements of reproducing the mean, variance, skewness, and first order autocorrelation coefficient is the first-order Markov process, given by

$$x_{i+1} = \bar{x} + \rho_x(1)(x_i - \bar{x}) + t_{i+1}\sigma_x\sqrt{1 - \rho_x^2(1)}$$

where x_i is the time series being simulated, \bar{x} is the mean of the time series, $\rho_x(1)$ is the one-lag autocorrelation coefficient, t_{i+1} is a standard normal random deviate, and σ_x is the standard deviation of the time series. Implementation of the first order Markov process requires estimation of the mean, standard deviation, and one-lag autocorrelation coefficient, and random generation of standard normal deviates.

Application of the first-order Markov model to log transformed data requires a correction so that the model preserves the statistics of the original data rather than the statistics of the log transformed data. The correction has the form

$$y_i = \ln(x_i + \alpha)$$

and the correction factor α is chosen such that the statistics of the original data set are reproduced. Following the procedures cited by Haan (p. 295, 1977) yields $\alpha = -186298$ AF. Monte Carlo simulations were done to test the performance of the correction. Five thousand values were generated using normally distributed runoff, lognormally distributed runoff with the correction, and lognormally distributed runoff without the correction. The statistics of these simulations were computed and compared to the statistics of the original data (Table 5). The mean values and standard deviations of all of the simulated runoff time series compare well with the original data, however only the corrected simulation reproduces the both skewness and first order correlation coefficient of the original data.

Table 5. Statistics of original and simulated Owens Valley runoff.					
	Original data	Simulated with	Simulated with lognormal	Simulated with	
		normal distribution	distribution and correction	lognormal distribution	
Mean (AF)	426205	422356	427524	429828	
Standard dev. (AF)	155402	156603	156822	157184	
Skewness	0.77748	-0.05652	0.74668	1.0860	
One-lag	0.141614	0.14208	0.14220	0.24684	
autocorrelation					

Development of additional MLRM for wells for predicting water table fluctuations at permanent monitoring sites.

In order to develop the ability to predict water table fluctuations at vegetation monitoring sites, it is desirable to develop MLRM for wells near monitoring sites, but proximity or relation to vegetation monitoring sites has not heretofore been one of the criteria for choosing wells for MLRM development (Harrington, 1998; 1999). Data and regression diagnostics for several wells that appear favorably situated for developing this capability are presented below (Table 6) and in Appendix 3. The wells were chosen by comparing the potential indicator well hydrograph to the monitoring well at the vegetation monitoring site; if the hydrographs were parallel for their common period of record, the well was considered useful for predicting fluctuations at the monitoring site. Additional work, not presented here, is necessary to relate water table fluctuations at the indicator wells to fluctuations at the vegetation monitoring site. Regression models were developed for the following wells: V271 (Laws wellfield), 572T (Big Pine wellfield), 507T (Thibaut Sawmill wellfield), and V097 (Bairs George wellfield).

LADWP wells that have a "V" designation are usually deep monitoring wells. Use of V-designated wells in the Laws and Bairs George wellfields is justified by the close correspondence between the hydrographs of the potential indicator well and nearby shallow wells situated at the vegetation monitoring site. Well V271 is over 195 ft deep according to LADWP's well database, however its well log indicates it was drilled to 113 ft and screened from 91 to 111 ft. Well V097 was drilled to 321 ft and its screened interval is unknown.

Well	Ν	\mathbb{R}^2	SE (ft)	Regression	n coefficients
V271	28	0.871	4.380	Intercept	2360.1
				Init. head	0.42443
				Pumping	-0.0004362
				Canal flows	0.0003883
572T	14	0.861	1.990	Intercept	2171.6
				Init. head	0.44770
				Pumping	-0.0001993
				OV runoff	0.00001179
507T	22	0.929	0.469	Intercept	1082.0
				Init. head	0.71572
				Pumping	-0.0001489
				OV runoff	0.0000013071
V097	28	0.871	3.239	Intercept	2686.3
				Init. head	0.29496
				Pumping	-0.0025717
				OV runoff	0.000010172

Table 6. Regression diagnostics and coefficients for additional indicator wells.

Conclusions and Recommendations

1. Use of the McNally canals as a predictor variable provides both better model performance and a more sound hydrological basis for Laws area MLRM. Diversions from the Owens River into the upper and lower McNally canals should be used as a predictor variable in these models in place of Owens Valley runoff.

2. Prediction intervals based on analytical methods and those based on bootstrap resampling provide similar estimates of uncertainty in MLRM predictions. Either method is suitable for evaluation of MLRM results. The choice of method can be left to convenience of the modeler, for example in MLRM applications where Monte Carlo methods are used to simulate runoff for multiple years into the future, it may be easier to implement bootstrap based methods; alternatively, in simple applications of the MLRM to make predictions one year into the future, use of the analytical method will provide faster model run times and perhaps be more familiar to other parties examining the model results.

3. For multiple year MLRM simulations, the method presented here for generating time-series of Owens Valley runoff reproduced the mean, standard deviation, skewness, and one-lag coefficient of autocorrelation, and is recommended for generating time series of autocorrelated lognormally distributed Owens Valley runoff.

4. MLRM were developed for wells V271, 572T, 507T, and V097. These models had adequate regression diagnostics, and may prove useful in developing linkages between indicator wells and permanent vegetation monitoring sites.

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Appendix 1: Regression model data for Laws wellfield indicator wells

This appendix contains data used for development of multiple linear regression models in the Laws wellfield using diversions from the Owens River into the McNally canals. Initial water table is the elevation above sea level of the water table measured during April of the year in the first column; pumping is runoff-year (April 1 through March 31) pumping for the Laws wellfield (acre feet); diversions to canals are the runoff-year diversions from the Owens River into the upper and lower McNally canals (acre feet) at the OVPA station; final water table is the water table elevation at the end of the runoff year. The fifth column is regressed against the second, third and fourth columns. The data were provided by LADWP.

Monitoring well 107T; RP elevation: 4156.1 ft; Land surface elevation: 4154.8 ft					
Year	Initial water table	Pumping	Diversions to	Final water table	
			canals		
1972	4126.75	28345	0	4117.09	
1973	4117.09	15974	5234	4119.23	
1976	4126.55	16285	0	4121.95	
1977	4121.95	15038	679	4119.32	
1978	4119.32	945	18367	4126.80	
1979	4126.80	17933	6861	4120.55	
1980	4120.55	1251	29132	4132.28	
1981	4132.28	25313	3290	4121.01	
1982	4121.01	1388	41570	4135.52	
1983	4135.52	1113	32492	4137.25	
1984	4137.25	7403	6589	4134.80	
1985	4134.80	17369	4117	4129.60	
1986	4129.60	8600	28204	4131.90	
1987	4131.90	38241	0	4119.00	
1998	4121.60	483	29410	4132.60	
1999	4132.60	1674	0	4129.60	
2000	4129.60	3975	2435	4127.98	

Monitoring well 436T; RP elevation: 4107.5; Land surface elevation: 4106.3					
Year	Water table	Pumping	Diversions to	Final water table	
	elevation		canals		
1976	4095.23	16285	0	4091.86	
1977	4091.86	15038	679	4090.75	
1978	4090.75	945	18367	4095.60	
1979	4095.60	17933	6861	4093.65	
1980	4093.65	1251	29132	4099.62	
1981	4099.62	25313	3290	4094.73	
1982	4094.73	1388	41570	4102.24	
1983	4102.24	1113	32492	4101.53	
1984	4101.53	7403	6589	4100.00	
1985	4100.00	17369	4117	4097.40	
1986	4097.40	8600	28204	4099.90	
1987	4099.90	38241	0	4094.20	
1988	4094.20	38841	3743	4090.30	
1989	4090.30	34785	173	4088.70	
1993	4089.10	12618	18082	4092.80	
1994	4092.80	16187	26	4092.10	
1995	4092.10	8249	22797	4096.60	
1996	4096.60	11199	0	4094.80	
1997	4094.80	2951	4892	4096.00	
1998	4096.00	483	29410	4100.50	
1999	4100.50	1674	0	4098.70	
2000	4098.70	3975	2435	4098.14	

Monito	Monitoring well 438T; RP elevation: 4142.1 ft; Land surface elevation: 4138.9 ft					
Year	Initial water table	Pumping	Diversions to	Final water table		
			canals			
1976	4129.44	16285	0	4127.66		
1977	4127.66	15038	679	4126.96		
1978	4126.96	945	18367	4131.21		
1979	4131.21	17933	6861	4128.16		
1980	4128.16	1251	29132	4133.26		
1981	4133.26	25313	3290	4128.09		
1982	4128.09	1388	41570	4136.37		
1983	4136.37	1113	32492	4134.97		
1984	4134.97	7403	6589	4133.2		
1985	4133.2	17369	4117	4131.9		
1986	4131.9	8600	28204	4132.4		
1987	4132.4	38241	0	4125.3		
1988	4125.3	38841	3743	4122.0		
1989	4122.0	34785	173	4122.4		
1990	4122.4	16933	0	4122.9		
1991	4122.9	10949	0	4123.7		
1992	4123.7	10562	0	4124.6		
1993	4124.6	12618	18082	4124.7		
1994	4124.7	16187	26	4124.7		
1995	4124.7	8249	22797	4127.5		
1996	4127.5	11199	0	4126.3		
1997	4126.3	2951	4892	4125.1		
1998	4125.1	483	29410	4131.3		
1999	4131.3	1674	0	4128.1		
2000	4128.1	3975	2435	4130.08		

Monito	Monitoring well 490T;RP elevation: 4078.3 ft; Land surface elevation: 4077.3 ft				
Year	Initial water table	Pumping	Diversions to	Final water table	
	elevation		McNally canals	elevation	
1976	4059.85	16285	0	4058.39	
1977	4058.39	15038	679	4057.86	
1978	4057.86	945	18367	4061.81	
1979	4061.81	17933	6861	4061.19	
1980	4061.19	1251	29132	4064.33	
1981	4064.33	25313	3290	4062.48	
1982	4062.48	1388	41570	4067.34	
1983	4067.34	1113	32492	4068.26	
1984	4068.26	7403	6589	4065.0	
1985	4065.0	17369	4117	4063.6	
1986	4063.6	8600	28204	4067.1	
1987	4067.1	38241	0	4064.1	
1988	4064.1	38841	3743	4061.1	
1989	4061.1	34785	173	4058.2	
1990	4058.2	16933	0	4056.9	
1991	4056.9	10949	0	4056.4	
1992	4056.4	10562	0	4056.5	
1993	4056.5	12618	18082	4057.9	
1994	4057.9	16187	26	4058.2	
1995	4058.2	8249	22797	4061.9	
1996	4061.9	11199	0	4061.1	
1997	4061.1	2951	4892	4060.3	
1998	4060.3	483	29410	4062.8	
1999	4062.8	1674	0	4062.0	
2000	4062.0	3975	2435	4063.39	

Monito	Monitoring well 492T; RP elevation: 4130.1 ft; Land surface elevation: 4128.4 ft				
Year	Initial water table	Pumping	Diversions to	Final water table	
			canals		
1977	4074.47	15038	679	4073.76	
1978	4073.76	945	18367	4093.66	
1979	4093.66	17933	6861	4082.93	
1980	4082.93	1251	29132	4100.18	
1981	4100.18	25313	3290	4086.39	
1982	4086.39	1388	41570	4104.65	
1983	4104.65	1113	32492	4106.91	
1984	4106.91	7403	6589	4102.7	
1985	4102.7	17369	4117	4091.3	
1986	4091.3	8600	28204	4097.7	
1987	4097.7	38241	0	4081.2	
1988	4081.2	38841	3743	4072.5	
1993	4079.6	12618	18082	4088.2	
1994	4088.2	16187	26	4085.8	
1995	4085.8	8249	22797	4092.5	
1996	4092.5	11199	0	4090.0	
1997	4090.0	2951	4892	4093.5	
1998	4093.5	483	29410	4102.9	
1999	4102.9	1674	0	4101.1	
2000	4101.1	3975	2435	4101.05	

Monitoring well 493T; RP elevation: 4133.2 ft; Land surface elevation: 4131.6 ft					
Year	Initial water table	Pumping	Diversions to	Final water table	
			canals		
1977	4093.08	15038	679	4090.55	
1978	4090.55	945	18367	4107.35	
1979	4107.35	17933	6861	4102.39	
1980	4102.39	1251	29132	4116.78	
1981	4116.78	25313	3290	4107.12	
1982	4107.12	1388	41570	4122.72	
1983	4122.72	1113	32492	4122.66	
1984	4122.66	7403	6589	4118.6	
1985	4118.6	17369	4117	4110.8	
1986	4110.8	8600	28204	4117.8	
1987	4117.8	38241	0	4103.0	
1988	4103.0	38841	3743	4094.2	
1989	4094.2	34785	173	4082.1	
1990	4082.1	16933	0	4083.7	
1991	4083.7	10949	0	4088.3	
1992	4088.3	10562	0	4087.4	
1993	4087.4	12618	18082	4103.2	
1994	4103.2	16187	26	4097.7	
1995	4097.7	8249	22797	4106.5	
1996	4106.5	11199	0	4100.5	
1997	4100.5	2951	4892	4105.0	
1998	4105.0	483	29410	4118.8	
1999	4118.8	1674	0	4114.2	
2000	4114.2	3975	2435	4112.7	

Appendix 2. Owens Valley runoff-year runoff, 1935-1999.

Runoff year is April 1 - March 31; runoff is in Acre feet. Data are from LADWP Totals and Means Report.

Year	Runoff	Year	Runoff	Year	Runoff
1935	384629	1960	216947	1985	428046
1936	457819	1961	213159	1986	658839
1937	532759	1962	418832	1987	280785
1938	765590	1963	465815	1988	258845
1939	393362	1964	274058	1989	261425
1940	441898	1965	421265	1990	215375
1941	648446	1966	300500	1991	265170
1942	522933	1967	626918	1992	254358
1943	499464	1968	299331	1993	441197
1944	365664	1969	885812	1994	276706
1945	533605	1970	380646	1995	637163
1946	446090	1971	321921	1996	558815
1947	334711	1972	276882	1997	513181
1948	255379	1973	466516	1998	618204
1949	299956	1974	465125	1999	358652
1950	324578	1975	377308		
1951	334580	1976	249678		
1952	588953	1977	216567		
1953	328270	1978	648737		
1954	332377	1979	411287		
1955	338978	1980	611023		
1956	507889	1981	351412		
1957	377966	1982	667114		
1958	532461	1983	792511		
1959	266496	1984	502366		



Figure A2.1. Owens Valley runoff-year runoff.

Well V271, Laws wellfield; R.P. elevation: 4128.19 ft.; Land surface elevation: 4125.2 ft.					
Year	Initial water table	Wellfield pumping	Diversions to	Final water table	
			Canals		
1972	4097.3	28629	0	4085.9	
1973	4085.9	22514	5234	4094.8	
1974	4094.8	8531	14623	4098.3	
1975	4098.3	8979	7242	4096.8	
1976	4096.8	14923	0	4091.1	
1977	4091.1	15661	679	4090.1	
1978	4090.1	7773	18367	4103.6	
1979	4103.6	6533	6861	4097.1	
1980	4097.1	12511	29132	4112.1	
1981	4112.1	12338	3290	4098.6	
1982	4098.6	14525	41570	4116.5	
1983	4116.5	1038	32492	4113.9	
1984	4113.9	6854	6589	4113.3	
1985	4113.3	10050	4117	4108.0	
1986	4108.0	9953	28204	4106.3	
1987	4106.3	25779	0	4093.2	
1988	4093.2	38025	3743	4080.2	
1989	4080.2	38167	173	4071.2	
1990	4071.2	28019	0	4079.5	
1991	4079.5	13700	0	4086.5	
1992	4086.5	8909	0	4087.8	
1993	4087.8	7601	18082	4096.1	
1994	4096.1	21001	26	4094.0	
1995	4094.0	7040	22797	4100.2	
1996	4100.2	11546	0	4096.6	
1997	4096.6	8349	4892	4102.0	
1998	4102.0	470	29410	4113.6	
1999	4113.6	1697	0	4110.1	
2000	4110.1	3975	2435		

Appendix 3. Data for additional regression wells.

Well 572T, Big Pine wellfield; R.P. elevation: 3944.54 ft.; Land surface elevation: 3944.3 ft.					
Year	Initial water table	Wellfield	OV runoff	Final water table	
		pumping			
1986	3932.4	25934	658839	3932.4	
1987	3932.4	48663	280785	3926.1	
1988	3926.1	42817	258845	3923.2	
1989	3923.2	33950	261425	3926.2	
1990	3926.2	20005	215375	3926.7	
1991	3926.7	24537	265170	3926.7	
1992	3926.7	24391	254358	3926.9	
1993	3926.9	23061	441197	3930	
1994	3930	24387	276706	3930.8	
1995	3930.8	24972	637163	3933.8	
1996	3933.8	22723	558815	3938.7	
1997	3938.7	24654	513181	3933.44	
1998	3933.44	22645	618204	3936.6	
1999	3936.6	19512	358652	3935.5	
2000	3935.5	25378	341464		

Well 507T, Thibaut Sawmill wellfield; R.P. elevation: 3807.35 ft.; Land surface elevation: 3806.6 ft.

Year	Initial water table	Wellfield pumping	OV runoff	Final water table
1979	3799.5	10518	411287	3800.2
1980	3800.2	13087	611023	3801.0
1981	3801.0	10511	351412	3801.4
1982	3801.4	10928	667114	3803.0
1983	3803.0	10698	792511	3803.1
1984	3803.1	10705	502366	3802.7
1985	3802.7	12744	428046	3803.3
1986	3803.3	14522	658839	3802.2
1987	3802.2	22018	280785	3800.7
1988	3800.7	20477	258845	3799.2
1989	3799.2	21930	261425	3798.0
1990	3798.0	16348	215375	3798.5
1991	3798.5	18156	265170	3798.2
1992	3798.2	16550	254358	3798.7
1993	3798.7	13737	441197	3798.8
1994	3798.8	14605	276706	3799.1
1995	3799.1	12528	637163	3800.0
1996	3800.0	15441	558815	3800.3
1997	3800.3	18043	513181	3800.7
1998	3800.7	12940	618204	3801.0
1999	3801.0	12525	358652	3800.9
2000	3800.9	12075	341464	3801.04
2001	3801.04			

Well V097, Bairs George wellfield; R.P. elevation: 3828.15 ft.; Land surface elevation: 3827.7 ft.

11.				
Year	Initial water table	Wellfield	OV runoff	Final water table
		pumping		
1972	3801.0	5673	276882	3790.5
1973	3790.5	2124	466516	3805.0
1974	3805.0	1387	465125	3800.9
1975	3800.9	3702	377308	3797.0
1976	3797.0	3894	249678	3796.6
1977	3796.6	5353	216567	3798.9
1978	3798.9	287	648737	3811.5
1979	3811.5	2720	411287	3807.4
1980	3807.4	8	611023	3818.1
1981	3818.1	2288	351412	3806.1
1982	3806.1	156	667114	3820.4
1983	3820.4	3	792511	3822.1
1984	3822.1	64	502366	3819.3
1985	3819.3	826	428046	3815.2
1986	3815.2	1140	658839	3813.9
1987	3813.9	6485	280785	3800.8
1988	3800.8	4602	258845	3802.3
1989	3802.3	3293	261425	3805.5
1990	3805.5	358	215375	3809.9
1991	3809.9	231	265170	3812.8
1992	3812.8	140	254358	3814.0
1993	3814.0	110	441197	3814.3
1994	3814.3	246	276706	3814.1
1995	3814.1	274	637163	3817.2
1996	3817.2	0	558815	3817.4
1997	3817.4	48	513181	3817.9
1998	3817.9	72	618204	3819.2
1999	3819.2	1	358652	3816.8
2000	3816.8	157	341464	