(760) 872-1168
FAX: (760) 873-5695
163 May Street
Bishop, CA 93514

COUNTY OF INYO
WATER DEPARTMENT

November 16, 1998

Multiple regression modeling of water table response to groundwater pumping and runoff

Robert Harrington, PhD

Introduction

One of the goals of the Los Angeles Department of Water and Power (LADWP) / Inyo County Long-term Water Agreement is to manage groundwater withdrawal such that significant decreases in live vegetation cover or undesired changes in plant community composition are avoided within groundwater dependent plant communities. Because groundwater dependent vegetation is sensitive to the depth of the water table, it is desirable to quantify the relationship between groundwater pumping and the expected response of the water table. There are three alternative methods of predicting changes in groundwater levels in response to pumping: (1) analytical methods, (2) numerical models, and (3) empirical models.

Analytical methods are limited in applicability to relatively simple hydrogeologic settings, such as predicting drawdown due to a single pumping well in an aquifer with relatively simple geometry; therefore, they are not well suited to the problem of predicting the effect of multiple pumping wells in a heterogeneous aquifer. Physically-based numerical models of groundwater flow are capable of simulating complex hydrogeological settings and have the potential for detailed simulation of water-table response to hydrologic variables, but require large amounts of information to characterize the hydrologic system, much of which is unknown, uncertain, or difficult to obtain. Results based on physically-based models are especially uncertain in highly heterogeneous hydrogeological systems such as the Owens Valley (Hollet et al., 1991). Furthermore, the development of numerical models is time consuming, costly, and not guaranteed to produce better results than a simpler empirical model.

Empirically-based models use the statistical correlation between observed hydrologic variables to determine the response of the system to various conditions. Multiple regression models are a type of empirical model that is widely used in hydrology in situations where sufficient historical data are available to develop statistical relationships between the variable of interest and the hydrologic variables that influence it. The theory of multiple regression methods is discussed in Haan (1977), Holder (1985), Hirsh et al. (1992), and Kufs (1992).

Applications of multiple regression methods to groundwater management are given in Hodgson (1978), Haggerty and Lippert (1982), and Zaltsberg (1983).

In the present study, regression models fulfill two objectives:

1. Prediction of future water table levels in response to runoff and pumping.
2. Determination of the relative influence of runoff and pumping on the water table at a given monitoring well location.

Because of the large amount of data available from shallow wells within the Owens Valley, multiple regression modeling is a promising approach, and the Inyo County Water Department (ICWD) has been engaged in an ongoing effort to develop multiple regression models (Williams, 1978; Woodward-Clyde, 1995; Jackson, 1996; Woodward-Clyde, 1997). This report describes the further development of multiple-regression-based models of shallow groundwater response to groundwater pumping beyond that described in the above-referenced reports. Two improvements have been made beyond the previous work: (1) the number of monitoring wells for which models were developed was expanded beyond previous efforts, thereby expanding the set of wells that can be used as indicator wells, and (2) a flexible and easily implemented method of assessing the uncertainty in model predictions was developed. In the following sections, the model structure and development are described, strategies and criteria for choosing applicable models are presented, a set of candidate wells for groundwater management is proposed, methods uncertainty analysis are demonstrated, and recommendations are made for management use of these models.

Model Structure and Development

In order to be a practical tool for predicting water-table response to pumping and recharge, the models must rely on variables that are readily available at the start of the runoff year. The models are based on water level measurements made in monitoring wells between April 1-30 for the years 1972-1995, run-off year pumping for individual wellfields (Figures 1 and 2), and runoff-year runoff for the entire Owens Valley (Figure 3). Hence, each model predicts the response of the water table in a monitoring well to pumping in the nearest wellfield and valley-wide runoff. Pumping and runoff are in acre-feet per runoff year (April 1 through March 31), and all hydrographs are in feet above mean sea level. Runoff is used as an independent variable rather than recharge, because recharge estimates require more assumptions and computation than runoff, and the strong causal correlation between runoff and recharge insures that runoff is a good surrogate for recharge. In mid-1998, LADWP revised its method of calculating total Owens Valley runoff, which led to decreased annual runoff on the order of 10000 acre feet. This may necessitate recalculation of regression coefficients in the future when the models are used for management purposes, however changes in the computation of runoff do not significantly affect the model selection process. Only test wells with six or more years of data were modeled. The location of LADWP wellfields in the Owens Valley and the location of groundwater-dependent land cover are shown in Figure 4. Wellfield pumping totals and water levels in shallow monitoring wells were taken from LADWP monthly well reports, and the well-read on or following April 1 was taken as the water level at the start or end of the runoff year. If there was no well-read between April 1-30, that year was considered as missing data and not used in the regression analysis. Data from dry wells were excluded from the data set. In 1977, LADWP deepened many of the shallow wells. Hydrographs of these wells were examined, and if deepening the well induced a sudden change in water level, data prior to deepening were excluded. The regression computations were done using Microsoft Excel version 8.0.

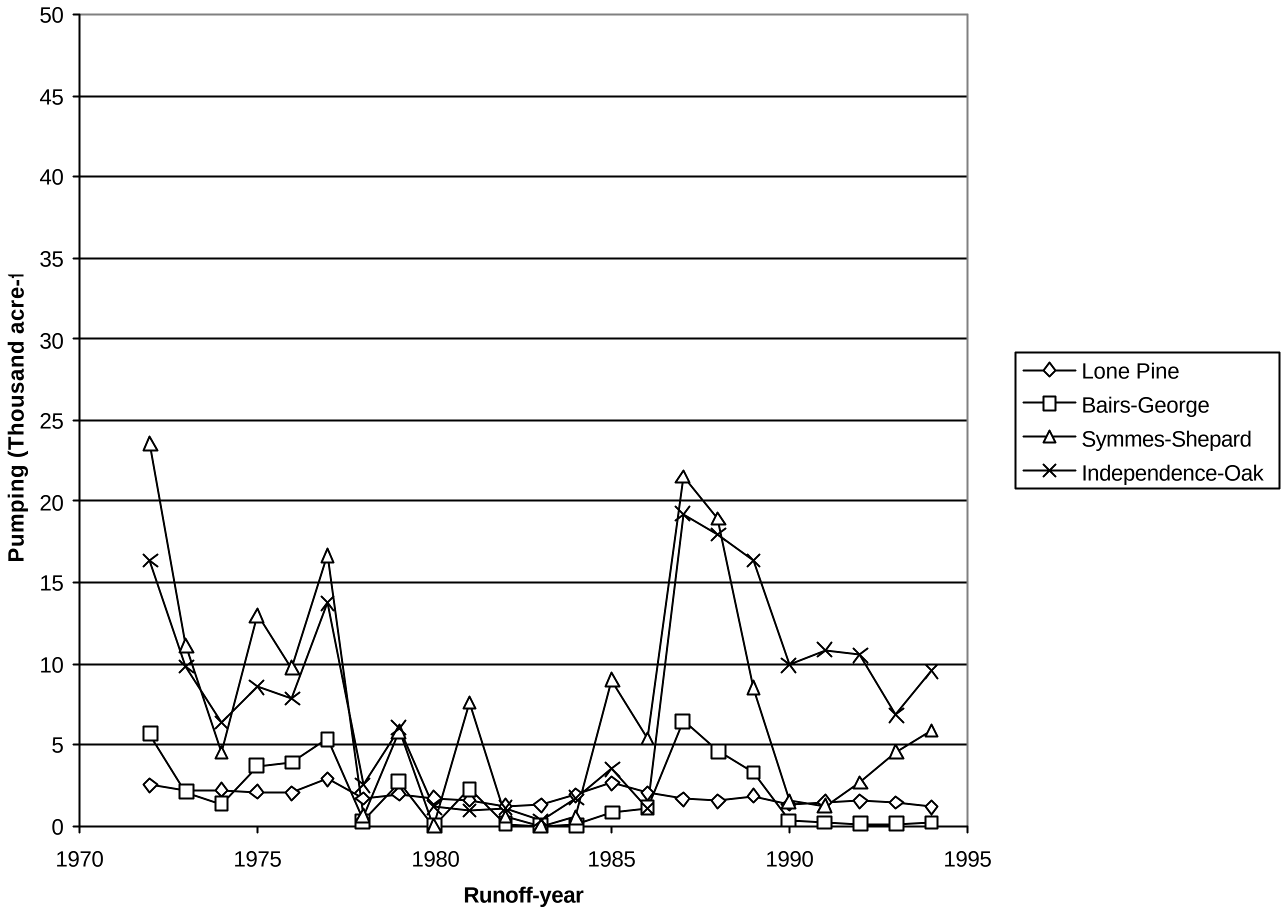


Figure 1. Runoff-year pumping by wellfield.

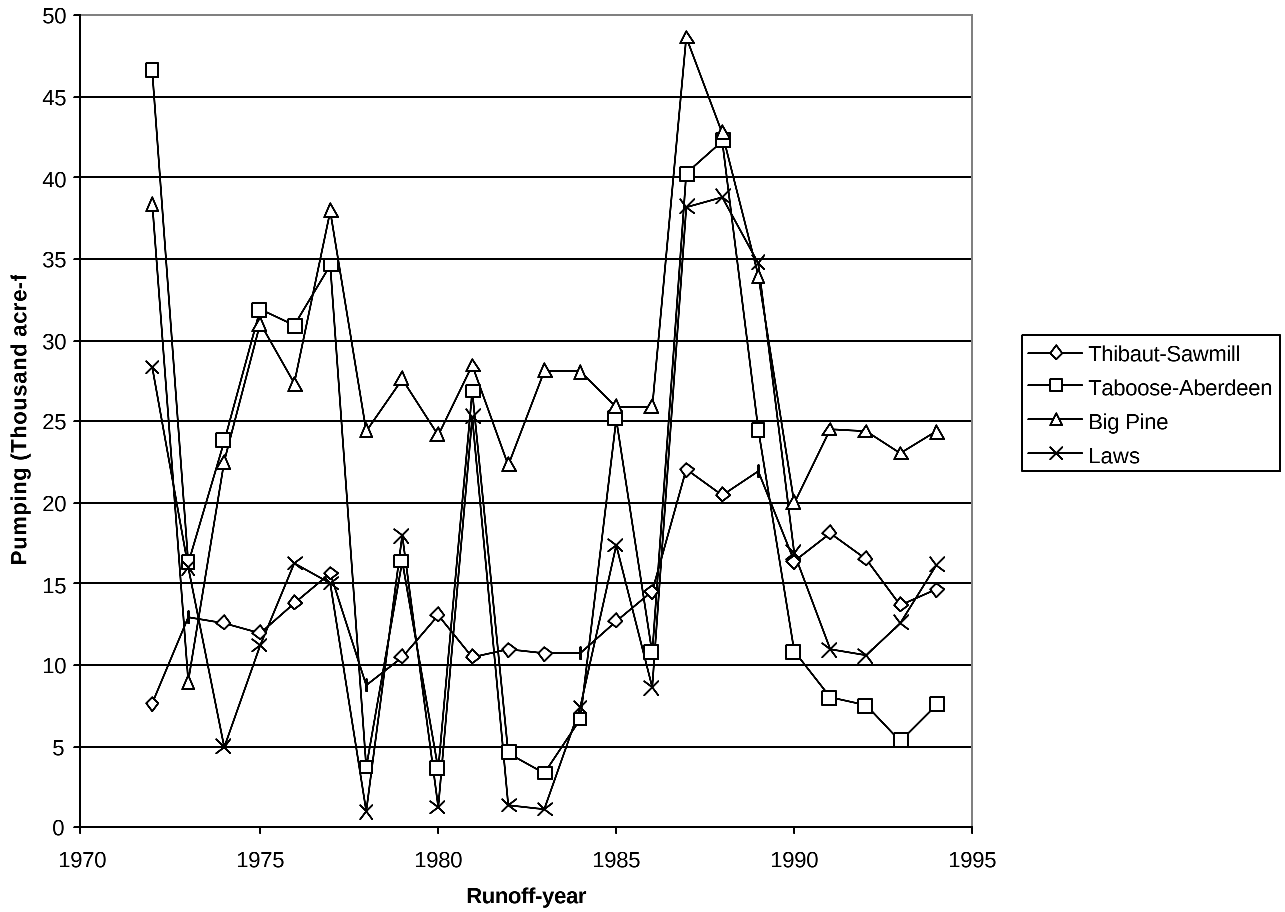


Figure 2. Runoff-year pumping by wellfield.

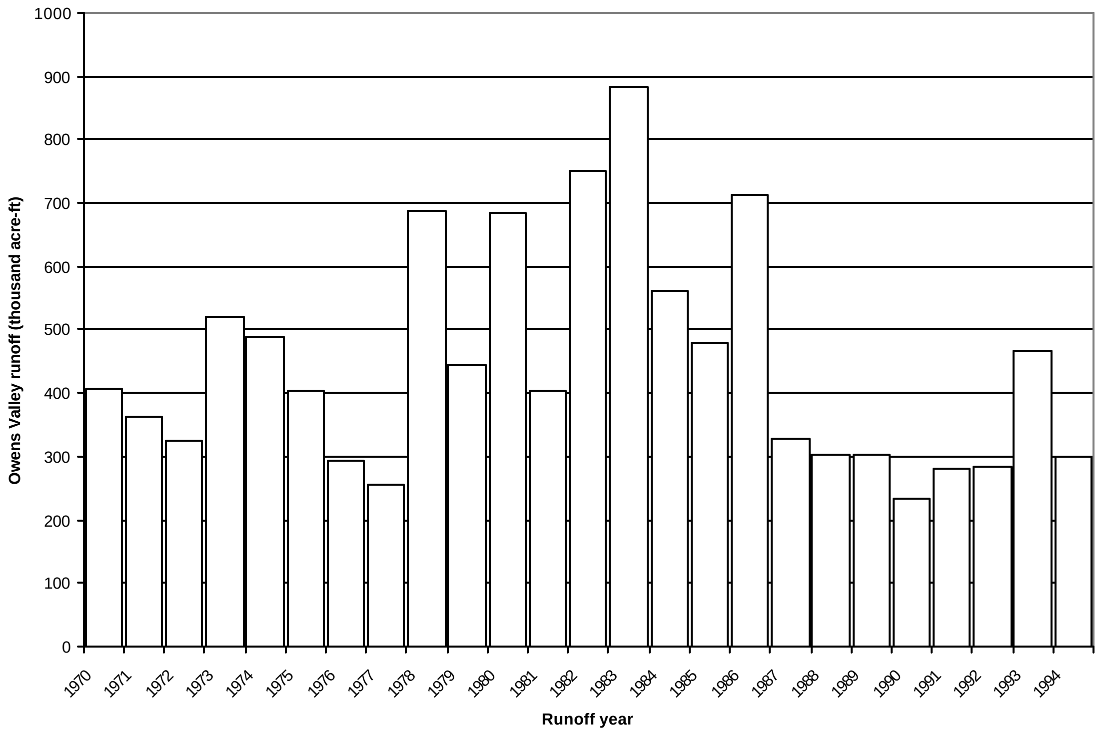


Figure 3. April 1-March 31 Owens Valley runoff.

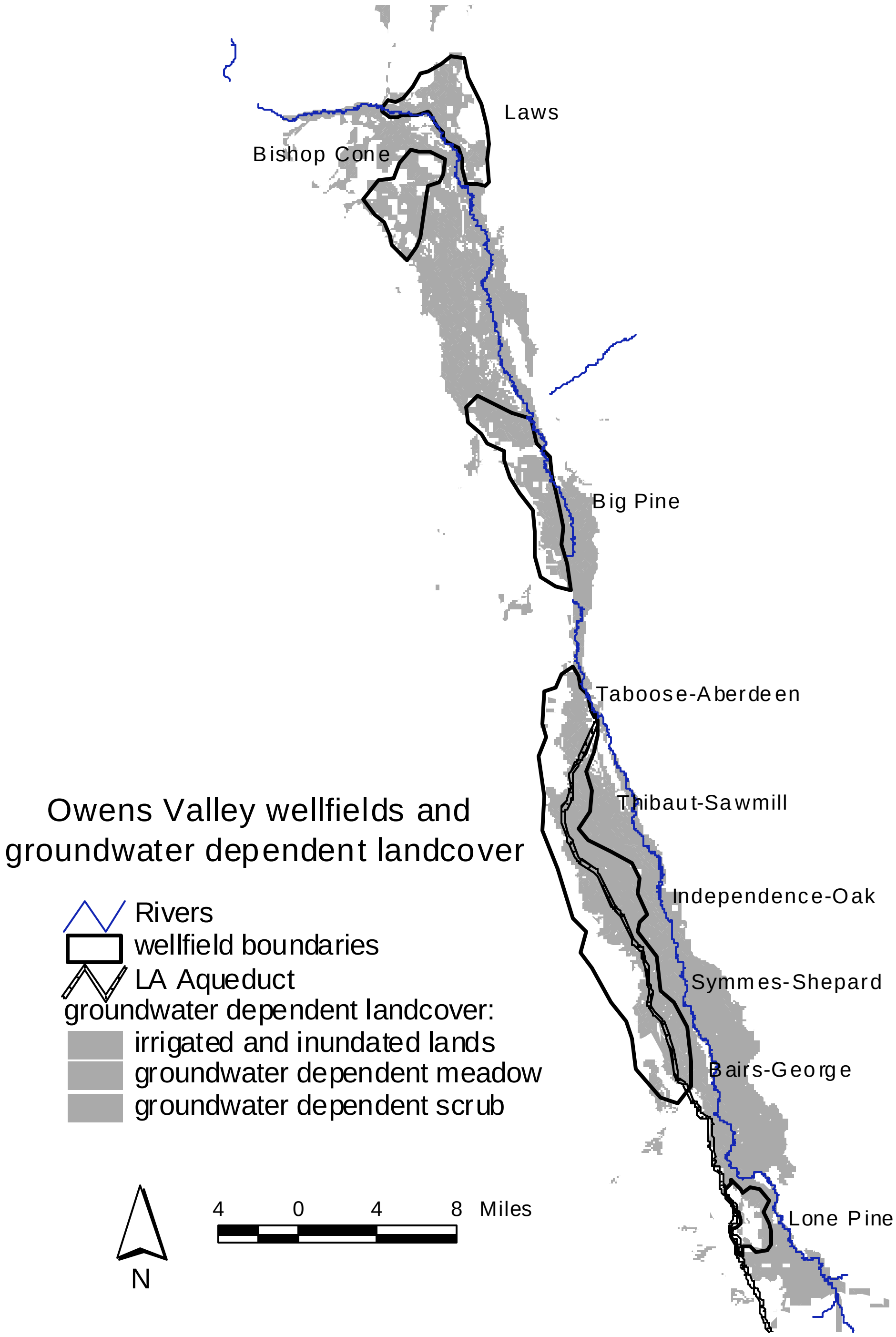


Figure 4. Locations of wellfields and groundwater dependent vegetation.

Three models were developed for each shallow well. The first model (model 1) uses three variables: initial hydraulic head in the monitoring well, annual pumping for the well field containing the well being modeled, and annual runoff for the entire Owens Valley, to model the hydraulic head at the end of runoff year:

$$h = b_0 + b_1 h_0 + b_2 P + b_3 R \qquad 1$$

where h is the modeled head at the end of the runoff year (feet above mean sea level), h_0 is the head at the start of runoff year (feet above mean sea level), P is pumping (acre-feet) in the well field nearest the shallow monitoring well being modeled, and R is valley-wide runoff (acre-feet). b_0, b_1, b_3, and b_4 are regression coefficients. The multiple regression method determines the regression coefficients that provide the closest fit between the data and equation 1. The second model (model 2) is the same as model 1, except runoff is not included as a variable:

$$h = b_0 + b_1 h_0 + b_2 P \qquad 2$$

Model 2 was developed because runoff estimates for the upcoming runoff year may not be available at the start of the runoff year, and because a model relying fewer variables is likelier to have more stable regression coefficients. It is also useful to compare models 1 and 2 to determine the importance of runoff as a driving variable. The third model (model 3) uses pumping and runoff to model the change in head:

$$h - h_0 = b_0 + b_1 P + b_2 R \qquad 3$$

Table 1 summarizes the input and output for each model. The main difference between model 3, and models 1 and 2 is that model 3 does not have the initial head in the model as an independent variable. Model 3 generally has lower multiple-R values, because it does not use the predictive information of the initial head, but it is useful for evaluating how much predictive power pumping and runoff provide independent of initial head. For a given well, the values of the coefficients are not the same between models, for example, for a given well, b_o in model 1 does not generally equal b_0 in model 2. Evapotranspiration (ET) is not included as an independent variable in the models, because it is difficult to forecast valley-wide ET for the upcoming runoff year. However, in models 1 and 2, the coefficient associated with h_0 is influenced by ET through a presumed tendency toward higher ET rates when the water table is shallow. This indirect modeling of ET is not present in model 3, because h_0 is not an independent variable.

Table 1. Summary of inputs and outputs for the three models.

	Independent variables (input)	Dependent variable (output)
Model 1	April 1 water level, wellfield pumping, valley-wide runoff	April 1 water level 1 year later
Model 2	April 1 water level, wellfield pumping	April 1 water level 1 year later
Model 3	Wellfield pumping and valley-wide runoff	Change in water level

Because multiple regression is an empirical method, many model formulations are possible and equally valid, and several alternative schemes have been used in other studies. To develop a valley-wide model of water table response to pumping in the Owens Valley, Williams (1978) used $1/h$ as an independent variable on the reasoning that this would better represent ET; however, the relationship used in the current models is consistent with the representation of ET used in Owens Valley numerical groundwater modeling efforts (Danskin, 1988; Danskin, in press). To assess the effects of rainfall and pumping on groundwater levels in Kentucky, Haggerty and Lippert (1982) reasoned that changes in aquifer storage result from the time-integrated effects of pumping and recharge, and therefore used cumulative deviation from mean pumping and precipitation rather than instantaneous values. While developing a monthly regression model, Hodgson (1978) found it necessary to use time-lagged variables to account for the travel-time of precipitation to the water table. To explore the applicability of these ideas, models using two and three year moving averages of runoff and pumping, and cumulative deviation from mean pumping and runoff were developed for wells 419T and 407T, but did not result in noticeably improved models. Transformation of pumping and runoff into zero-mean, unit-variance variables did not affect the quality of the models.

Models 1, 2, and 3 were developed for shallow monitoring wells in the Lone Pine, Bairs-George, Symmes-Shepard, Independence-Oak, Thibaut-Sawmill, Taboose-Aberdeen, Big Pine, and Laws wellfields. Due to the Hillside Decree, the Bishop Cone is subject to different management criteria than the rest of the Owens Valley, and was not included in this work. Regression results for indicator wells on the Bishop Cone are available elsewhere (Jackson, 1996). The number of data, coefficients (b_i), multiple-R's, standard errors, and t-statistic probabilities for each of the 170 wells that have been modeled are tabulated in Appendix 1.

Model evaluation

The models listed in Appendix 1 were evaluated to determine which will be most useful for water table management. Despite the routine nature of deriving regression coefficients, several issues arise when determining whether a model is statistically acceptable and useful for management:

Does the model do a good job of fitting the data? This question is addressed by the multiple correlation coefficient (multiple-R). It ranges between 0 and 1, and the closer to 1, the better the model fits the observations. When comparing one monitoring well to another, the multiple-R rather than standard error should be compared, because the magnitude of the standard error depends on the range of the data as well as the goodness of fit, whereas multiple-R is purely a measure of goodness of fit.

Is it a hydrologically reasonable model? Models where increasing pumping raises the water table or where increasing runoff lowers the water table are hydrologically unrealistic and were rejected.

Does each input variable influence the response variable? This question is addressed by the t-statistic and associated probability for each coefficient in the regression (Appendix 1). The probabilities listed in Appendix 1 are the probability that the estimated regression coefficient would be as large or larger than this, given that the true regression coefficient is equal to zero. Thus, a small probability indicates that the coefficient is significant (unlikely to be zero). When the standard error of model 2 is less than that of model 1, it suggests that the additional variable in model 1 (runoff) does not add significant information to the model. Kufs (1992) points out that violating the assumptions of independence of variables and homoscadasticity of errors that underlie multiple regression affect the apparent significance level of the t-statistic. These types of violations are somewhat unavoidable in real-world hydrologic data, so level of significance chosen to determine if a model is acceptable is somewhat arbitrary.

Can we expect the model to be useful for managing pumping? In cases where models 1 and 2 produce high multiple R values, but model 3 does not, it is likely that the predictive power in models 1 and 2 derives mainly from the information contained in the initial head (h_0). This problem is particularly acute in wells where the period of record is short and water levels have undergone monotonic change over the period of record Despite having high multiple-R's, these models may not be very useful for managing pumping, because the model relies mainly on the initial head to predict the next year's head. Well 622T (Independence-Oak Creek wellfield) is an example of such a well.

Are the model coefficients stable? If the addition of more data would substantially change the regression coefficients, they are unstable, hence, longer observational records result in more stable regression coefficients. Wells with fewer than six years of data were not modeled are not included in Appendix 1, and when evaluating models, those derived from longer records should be preferred. An associated problem is referred to as multicollinearity, where two or more of the independent variables are correlated, and thus contain the same information. This results in unstable (or in the worst case, non-unique) regression coefficients. The correlation coefficients given in Table 2 show an inverse relation between pumping and runoff in all wellfields, reflective of the historical management tendency toward somewhat greater pumping during low-runoff years. Variance inflation factors (see Hirsh et al. (1992)) were not computed for each variable in each model, however, the correlation coefficients in Table 2 suggest that multicollinearity is not a serious problem with these data.

Table 2. Correlation between pumping and Owens Valley runoff.

Wellfield	Correlation coefficient for pumping and runoff

Lone Pine	-0.16
Bairs-George	-0.50
Symmes-Shepard	-0.50
Independence-Oak Creek	-0.76
Thibaut Sawmill	-0.53
Taboose-Aberdeen	-0.55
Big Pine	-0.33
Laws	-0.66

Based on the above considerations, this scheme for choosing models that are acceptable for predicting water levels is proposed:

1. Are there six or more years of data? Reject if no.
2. Is the pumping coefficient negative? Reject if no.
3. Is the runoff coefficient positive? Reject if no.
4. Is the multiple-R value sufficiently large (>0.80)? Reject if no.
5. Are the coefficients significant (significance level < 0.10)? Reject if no.
6. For a given well, is model 1 significantly more powerful than model 2 (standard error of model 1 > standard error of model 2)? Reject model 1 in favor of model 2.

If a model meets the above criteria, the hydrogeologic setting of the well should be examined. Has the management of production wells or surface water in the proximity of the test well changed? Is the test well in an area of groundwater dependent vegetation? Is the well near pump equipped wells? Also, model 3 can be used to determine whether pumping and / or runoff predict changes in the water table. Choose models that seem to be representative of the hydrology and relevant to management.

Wells that meet criteria 1 through 7 are given in Table 3. Wells that have less than ten years of data or have been used as indicator wells are noted. Hydrologic circumstances that call into question the usefulness of a well, such as proximity to planned components of the Lower Owens River Project (LORP) are also noted. Model 3 provides some further insight into the hydrologic response of the water table. Some wells that are listed in Table 3 are not recommended as potential indicator wells based on low multiple-R or insignificance of pumping as a driving variable in model 3.

Table 3. Candidate indicator wells. Indicator wells and models derived from fewer than ten data are noted. “Weak model 3” indicates that model 3 either had multiple-R less than 0.6 or the regression coefficients were insignificant. “Deepened ‘77” indicates that the well was deepened in 1977.

WELL	MODEL	COMMENTS
Lone Pine wellfield		
393T	2	N=8, potential indicator well
588T	1	N=9, potential indicator well
360T	1	Potential indicator well
Bairs-George wellfield		
398T	1	Indicator well
399T	2	Potential indicator well
400T	2	Indicator well
444T	1	E of wellfield
596T	2	N=9, potential indicator well
597T	2	N=9, potential indicator well
598T	2	N=9, potential indicator well
653T	2	N=7, potential indicator well
Symmes-Shepard wellfield		
401T	1	Indicator well, deepened ‘77
402T	1	Potential indicator well, deepened ‘77
403T	1	Indicator well, deepened ‘77
404T	2	Indicator well
447T	1	Indicator well
510T	2	Potential indicator well
511T	2	Potential indicator well
602T	1	N=9, potential indicator well
641T	2	N=6, potential indicator well
649T	2	N=7, potential indicator well
9GA	2	N=9, potential indicator well

Table 3. Continued.

WELL	MODEL	COMMENTS
Independence-Oak Creek wellfield		
23T	1	Two nearby pump equipped wells retired, replacement sealed
374T	2	E of wellfield
382T	2	E of wellfield
405T	2	Weak model 3
406T	2	Potential indicator well
407T	2	Indicator well, deepened '77
408T	2	Indicator well
409T	2	Indicator well, flows occasionally, 42' deep, should be dropped as indicator, deepened '77
412T	2	Potential indicator well
450T	2	E of wellfield, weak model 3
450T	2	Potential indicator well
451T	2	E of wellfield, weak model 3
453T	2	Potential indicator well
509T	2	Weak model 3
546T	2	Potential indicator well
554T	2	N=9, potential indicator well
651T	1	N=7, potential indicator well
15GA	2	N=9, potential indicator well
7G	2	N=9, potential indicator well
Thibaut-Sawmill wellfield		
376T	2	Possibly affected by future LORP components
380T	2	Possibly affected by future LORP components
381T	1	Possibly affected by future LORP components
413T	2	Potential indicator well
414T	2	Potential indicator well
415T	2	Indicator well, deepened '77
454T	2	Potential indicator well
466T	1	Potential indicator, E of wellfield, deepened '77
507T	2	Possibly affected by LORP
52T	2	Potential indicator well
52AT	2	Potential indicator well
584T	2	N=9, potential indicator well
603T	1	N=7, possibly affected by LORP
Taboose-Aberdeen wellfield		
417T	2	Potential indicator well, deepened '77
418T	1	Indicator well, deepened '77
419T	1	Indicator well, deepened '77
421T	1	Indicator well, deepened '77
455T	2	E of wellfield, weak model 3
456T	2	E of wellfield, weak model 3
502T	1	Indicator well
504T	1	Potential indicator well
505T	2	Potential indicator well
506T	2	Potential indicator well
670T	2	N=9, potential indicator well

Table 3. Continued.

WELL	MODEL	COMMENTS
Big Pine wellfield		
425T	1	Indicator well, deepened '77
426T	1	Indicator well
429T	2	Weak model 3
469T	1	Potential indicator well
566T	1	N=9, potential indicator well
571T	1	N=9, potential indicator well, deepened '77
572T	2	N=9, potential indicator well
681T	2	N=8, potential indicator well
685T	1	N=8, potential indicator well
689T	2	N=8, weak model 3
690T	2	N=8, weak model 3
691T	2	N=8, weak model 3
17GC	1	N=9, potential indicator well
5G	2	N=8, potential indicator well
Laws wellfield		
107T	2	Potential indicator well
435T	2	Potential indicator well
436T	1	Indicator well
437T	2	Potential indicator well
438T	1	Potential indicator well
490T	2	Potential indicator well
491T	2	Potential indicator well
492T	1	Indicator well
493T	2	Potential indicator well
703T	2	N=8, weak model 3
704T	2	N=8, weak model 3
706T	1	N=8, potential indicator well

Model uncertainty

The most straightforward application of these models is in forecasting the water level at the start of the next runoff year, given a proposed level of wellfield pumping and an April 1 runoff forecast. Other applications include multi-year model runs to determine likely fluctuations in the water table under various pumping and runoff stresses. This section examines uncertainty in predicted water levels due to various sources of uncertainty implicit in the regression modeling.

There are four sources of uncertainty within predictions made using multiple regression models: (1) uncertainty due to errors in the measurement of input variables (such as initial head), (2) uncertainty in derived regression coefficients due to the limited extent of data, (3) uncertainty in input variables that are derived from forecasts rather than measurements (such as pumping or runoff forecasts), and (4) uncertainty due to the structure of the model (i.e., the linear regression model is not a complete representation of the real hydrologic system). In the models being developed here, measurements errors in the value of h_o are likely to be negligible compared to errors due to parameter uncertainty, model structure, and runoff forecast uncertainty. The uncertainty associated with predictions made by regression models can be assessed by Monte Carlo simulation. Monte Carlo simulation is a technique by which the uncertainty associated with a model is determined by repeatedly running the model with different sets of parameters or input, where the parameters or input are drawn from probability distributions; hence, implementation of the Monte Carlo method requires that the probability distribution of the simulated variable is known. An example of how to quantify uncertainty due to runoff variability in multi-year simulations was produced by Woodward-Clyde (1997).

Uncertainty in the regression coefficients can be evaluated by the bootstrap method of Monte Carlo simulation. The bootstrap method involves generating synthetic data sets that are repeatedly drawn from the observed data set and regression coefficients are computed for each synthetic data set. Hence, the observed data set is taken as the discrete probability distribution of the data. This produces a range of possible regression coefficients, and hence produces a range of predicted water levels. The bootstrap method is particularly suited to small data sets where the analytical form and parameters of the probability distributions are unknown. The bootstrap method of assessing model parameter uncertainty is summarized in Press et al. (1992).

Uncertainty in the model result due to the model structure is quantified in the standard error of the regression. The effect of this on model output can be assessed using Monte Carlo simulation by adding a normally distributed zero-mean random number with a standard deviation equal to the standard error of the regression to the model result.

Uncertainty in the model result due to uncertainty in runoff depends on how runoff is being input into the model. If the runoff is the forecast runoff for the present runoff year, the uncertainty is due to how much the April 1 runoff forecast is likely to deviate from the actual runoff. Alternatively, if the runoff is for a year beyond the current runoff year, the runoff is derived from the observed historical distribution of annual runoff. Clearly, the uncertainty associated with a future year's runoff is much greater than that due to errors in the current year's April 1 forecast.

The relative magnitude of the error due to each source of uncertainty vary from well to well due to differing amounts of data available for each well, the various hydrogeologic settings of the wells, and the different pumping schedules to which each wellfield has been subjected. As an example the relative importance the different sources of error, simulations of the response of well 419T to water level, pumping, and runoff were done incorporating each source of error separately in different simulations using model 1, and the resulting ranges of uncertainty are given in Table 4. The initial water level was 3827.38 ft msl, which was measured during the first week of April, 1998. The runoff used were the forecasts supplied with the LADWP pumping program for 1998. Uncertainty in the April 1 runoff forecast is largely due to the unknown post-April 1 precipitation; hence, water levels were computed for the median post April 1 precipitation, the 10% exceedence post-April 1 precipitation, and the 90% exceedence post-April 1 precipitation (603800, 653000, and 552000 AF respectively). For demonstration purposes, pumping was arbitrarily set at 20000 AF for the Taboose-Aberdeen wellfield. The uncertainty in forecast water level due to uncertainty in the regression parameters was derived by the bootstrap Monte Carlo simulation method, as described above. The range of uncertainty due to the unexplained component of the data variance was assessed by an adding a normally distributed random number to the regression equation, where the mean of the random number was equal to zero and the standard deviation was equal to the standard error of the regression. This quantifies the uncertainty in the prediction that would be present, even if the regression coefficients were known exactly.

The combined effect of uncertainty in the regression coefficients and unexplained variance was assessed by applying both methods described above simultaneously. The uncertainty in the runoff forecast was not included in the combined assessment of uncertainty, because the distribution of runoff forecast errors is not available, but such data could be compiled for future use. Each Monte Carlo simulation computed the forecasted water level 5000 times, and the resulting distribution of computed water levels yields the probability that a given water level will be met or exceeded. Convergence of the simulation statistics was monitored by observing the change in means and standard deviations of the model prediction and regression coefficients. These statistics stabilized after a few thousand iterations, indicating that simulations using 5000 iterations are stable and reproducible.

Table 4 suggests that for well 419T, the greatest source of error is due to the unexplained variance, less error is imparted by parameter uncertainty, and the smallest source of error is due to error in the April 1 runoff forecast. It is worth noting that even though runoff is a significant variable at well 419T, uncertainty in runoff imparts a relatively small error to the prediction.

Table 4. Monte Carlo simulation of well 419T. 90% of the modeled responses exceeded the 90% level, 50% exceeded the median, and 10% exceeded the 10% level.

Source of uncertainty	90%	Median	10%	Range (90%-10%) (ft.)
Runoff forecast	3825.42	3825.87	3826.29	0.87
Regression coefficients	3825.41	3825.92	3826.65	1.24
Unexplained variance	3824.41	3825.86	3827.33	2.92
Regression coefficients and unexplained variance	3824.39	3825.96	3827.60	3.21

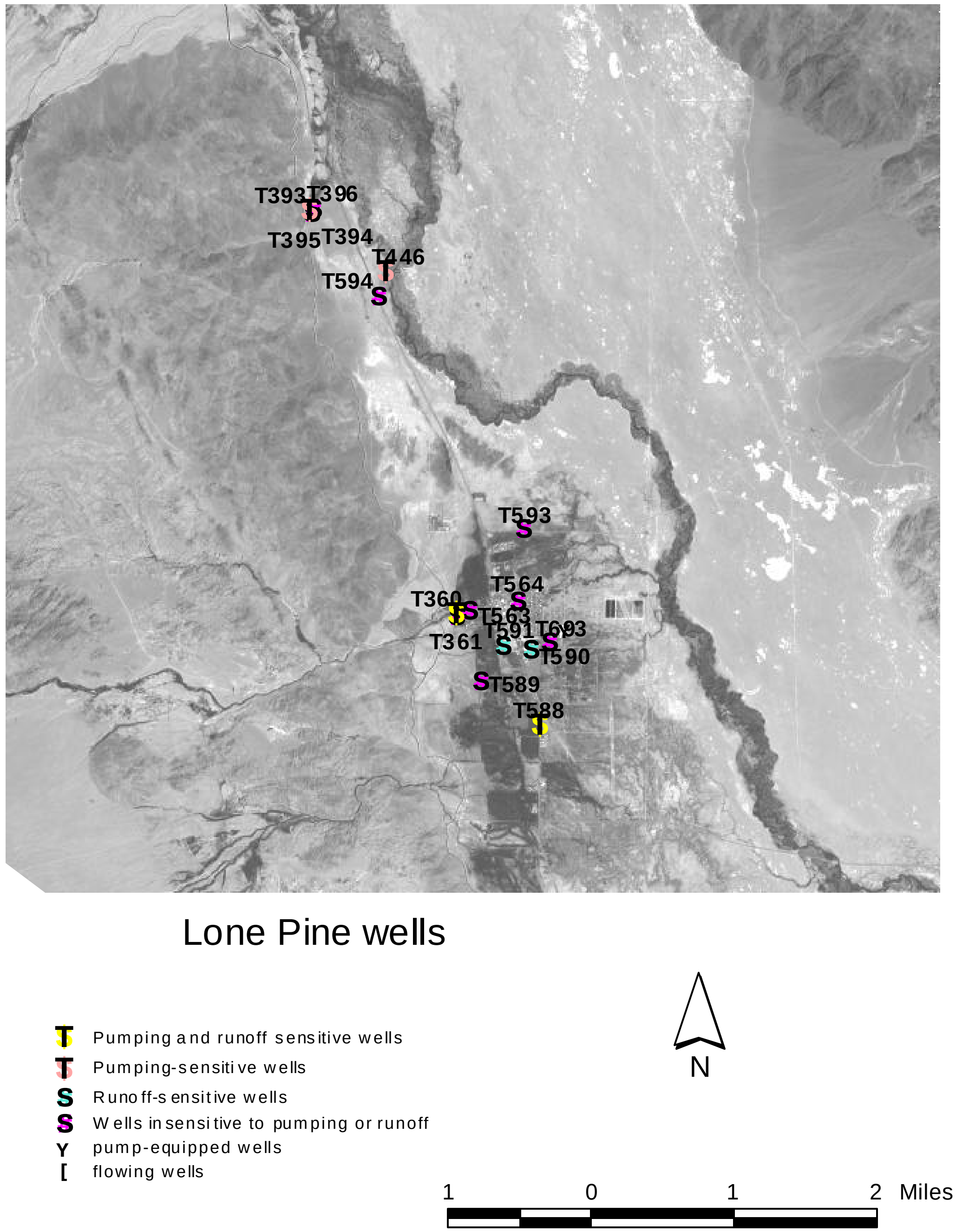
Forecasting water level fluctuations beyond the present runoff year adds two additional sources of uncertainty. First, the runoff must be forecast using the historical distribution of runoff, rather than the current year's snow-survey-based runoff estimate. Second, the initial water level for subsequent years is taken from the previous year's model result, thereby propagating errors from one year to the next. To assess the degree to which the model uncertainty propagates through multi-year simulations, water levels in well 419T were modeled for four years of 20000 and 5000 AF Taboose-Aberdeen wellfield pumping. 1998 initial conditions and the 1998 runoff forecast for the first year, and the final three years runoff were randomly generated from a lognormal distribution based on the 1945-1995 Owens Valley runoff record.

Table 5. Multi-year simulations of well 419T subject to 20000 and 5000 AF pumping. 90%, median, and 10% refer to exeedence levels among the simulation results.

	90%	Median	10%	Range (10%-90%) (ft.)
	20000 AF/year pumping			
End of first year	3824.42	3825.99	3827.56	3.14
End of second year	3821.00	3823.48	3826.42	5.42
End of third year	3818.77	3821.84	3825.38	6.61
End of fourth year	3817.27	3820.60	3824.32	7.05
	5000 AF/year pumping			
End of first year	3828.31	3829.92	3831.58	3.27
End of second year	3827.61	3830.36	3833.49	5.88
End of third year	3827.33	3830.72	3834.40	7.07
End of fourth year	3827.32	3830.88	3835.14	7.82

Results

Figures 5 through 11 show the locations of monitoring wells, pump equipped wells, and flowing wells. Water level fluctuations in an individual well may be affected by a variety of local influences such as irrigation, surface water flows, phreatophytic vegetation, hydrostratigraphic variability, or nearby pumping or flowing wells. However, the effect of local influences is not easily predicted, for example, wells 454T and 685T are both near managed surface water conveyances, yet both show significant influence from pumping. Despite local influences, the regression model results show some consistent spatial patterns in the sensitivity of the water table to pumping and recharge. The Lone Pine wellfield has historically had low levels of pumping (Figure 1), which is reflected in the regression models as an absence of sensitivity to pumping (Figure 5 and Appendix 1). Monitoring wells in the Bairs-George, Symmes-Shepard, Independence-Oak, Thibaut-Sawmill, and Taboose-Aberdeen wellfields have a general tendency to be sensitive to pumping within the wellfields along the western edge of the valley bottom, and to be sensitive to runoff in the central part of the valley (Figures 6 through 9). The spatial patterns of sensitivity to pumping and runoff in the Big Pine and Laws wellfields show no clear patterns (Figures 10 and 11). Monitoring wells that are sensitive to both pumping and runoff tend to occur in clusters, notably in the Manzanar area, near the LA aqueduct intake, north of Steward Lane, and east of Fish Springs Road. Monitoring wells that did not satisfy the criteria for acceptable models were rather uniformly distributed throughout the valley.



Danskin (in press) performed a sensitivity analysis on a numerical groundwater flow model of the Owens Valley and, as expected, found that monitoring wells located in recharge areas were sensitive to recharge, and wells located in wellfields were sensitive to pumping. He also found that, to a surprising degree, wells located in recharge areas were also sensitive to pumping, and concluded that pumping was the dominant driving variable in water table levels in the Owens Valley. This result is consistent with the large number of regression models for which pumping was found to be a statistically significant influence on water table fluctuations (Appendix 1).

Figure 5. Lone Pine monitoring, pump equipped, and flowing wells.

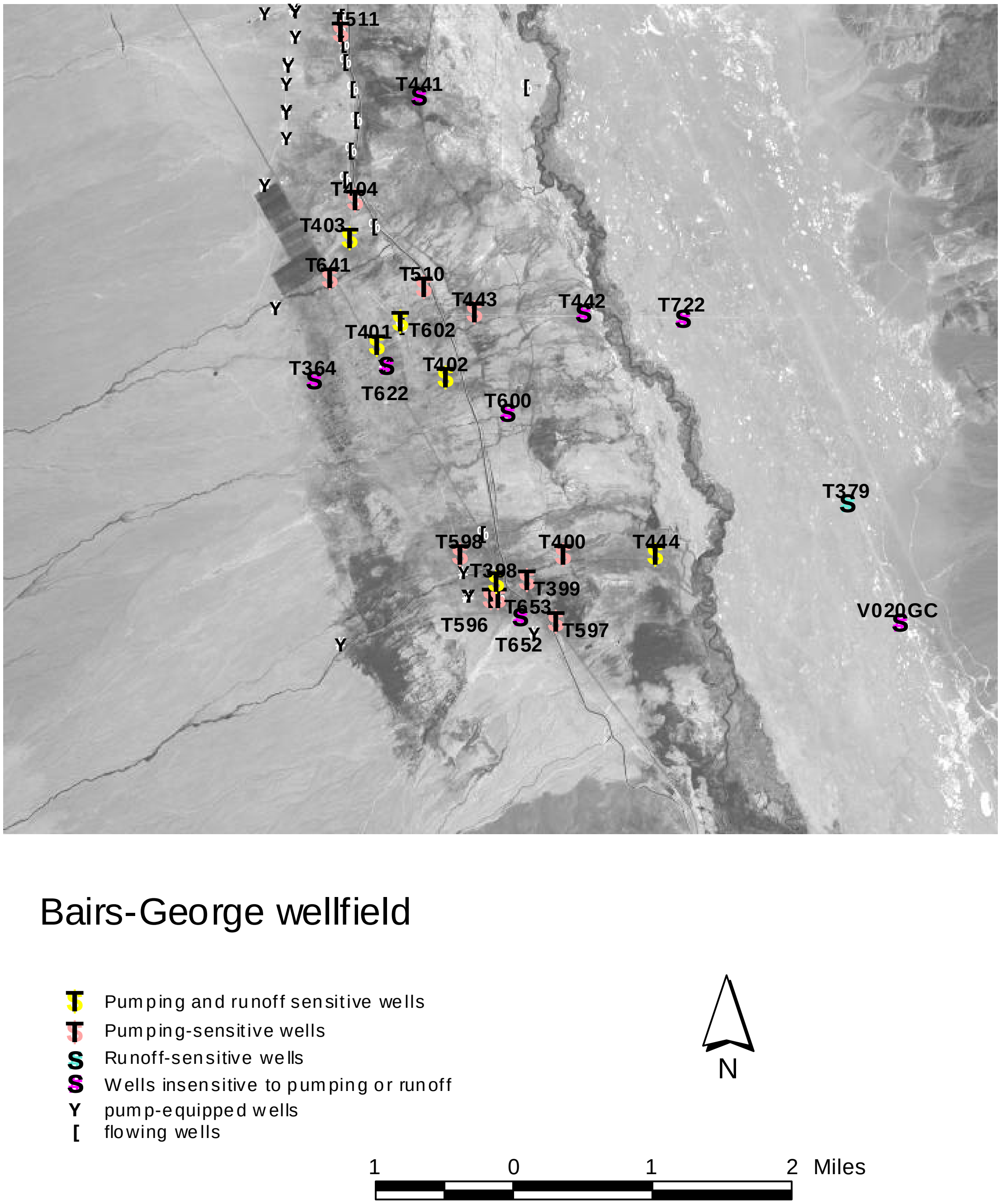


Figure 6. Bairs-George wellfield monitoring, pump equipped, and flowing wells.

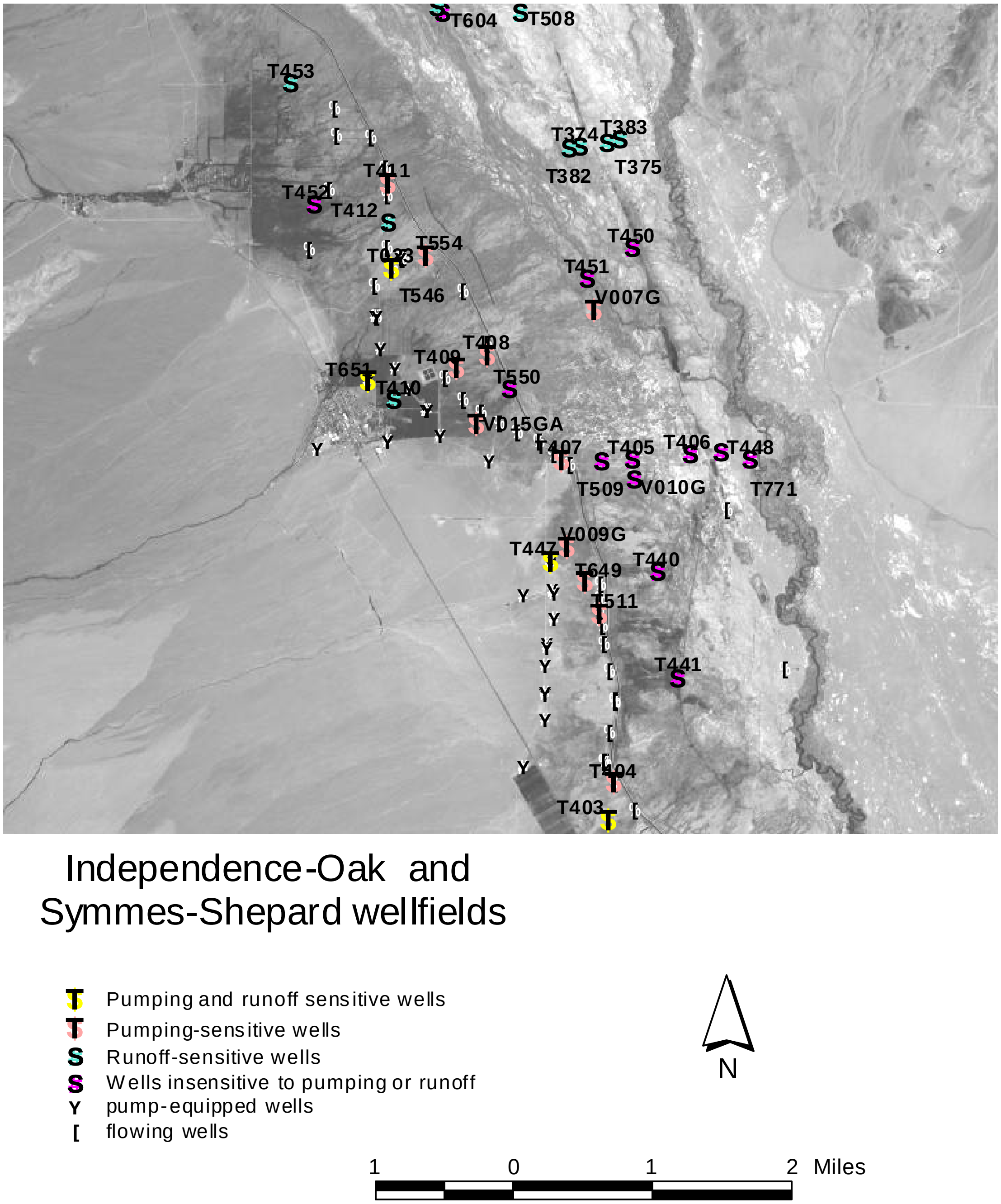


Figure 7. Symmes-Shepard and Independence-Oak Creek wellfield monitoring, pump equipped, and flowing wells.

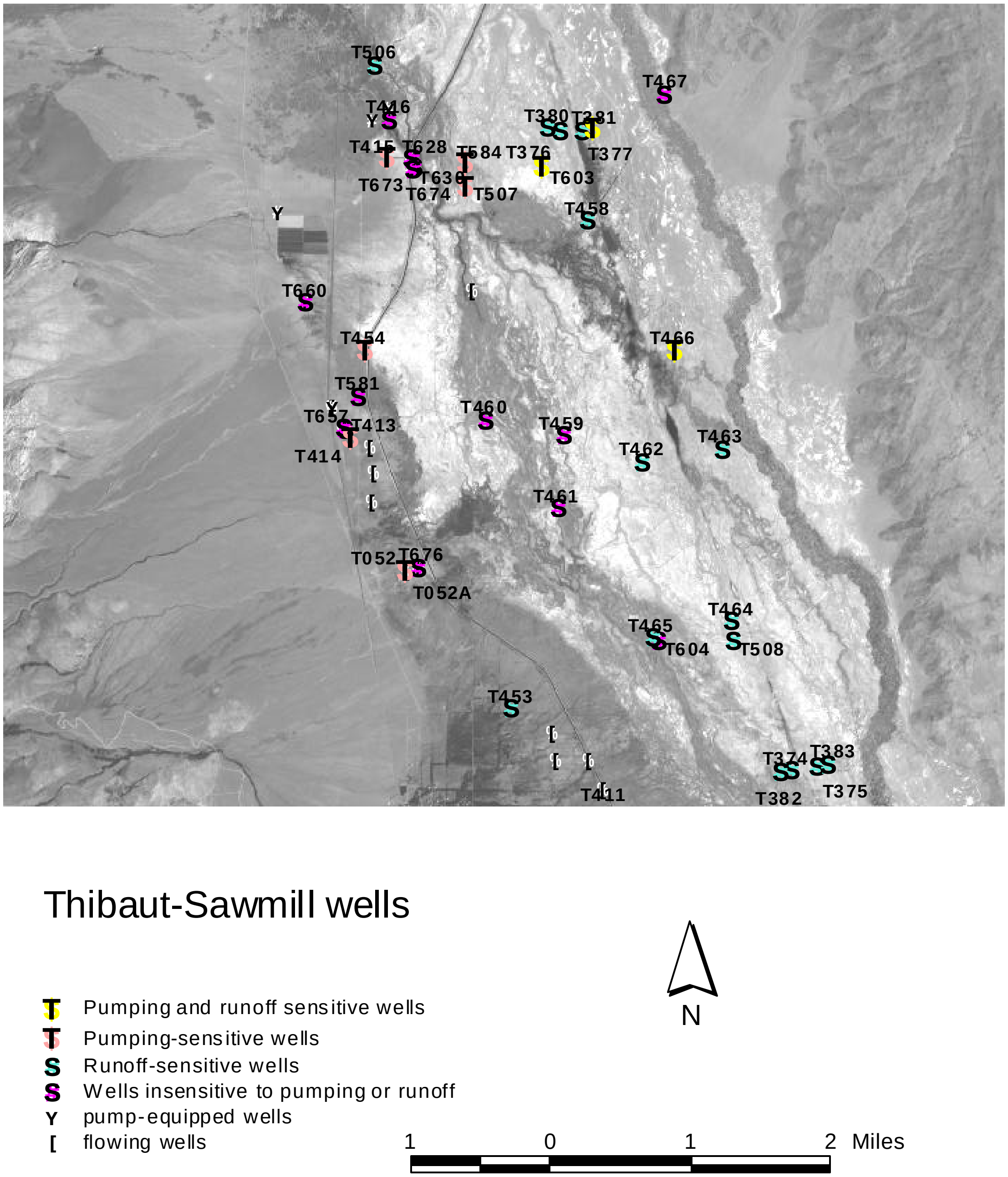


Figure 8. Thibaut-Sawmill wellfield monitoring, pump equipped, and flowing wells.

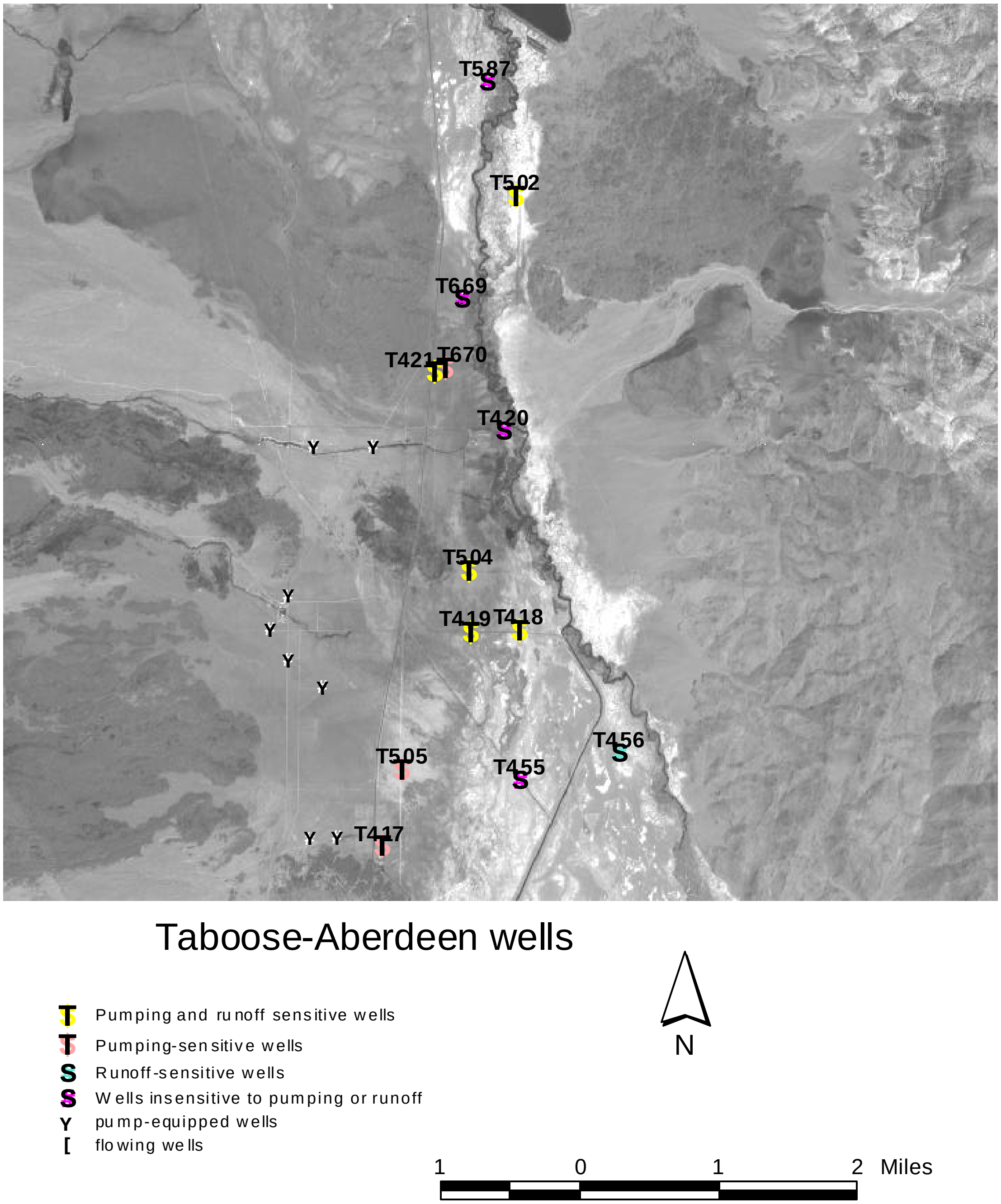


Figure 9. Taboose-Aberdeen monitoring, pump equipped, and flowing wells.

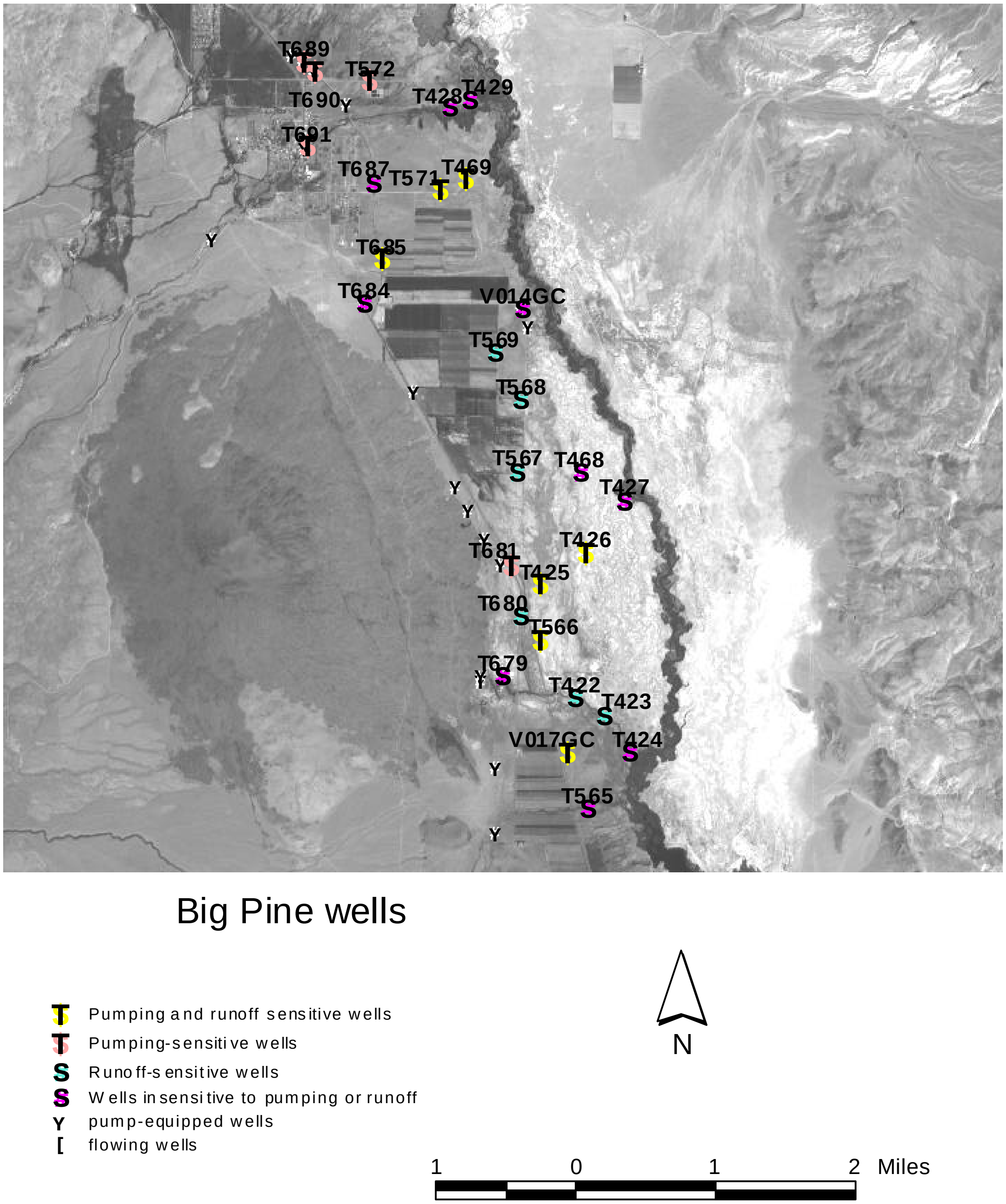


Figure 10. Big Pine monitoring, pump-equipped, and flowing wells.

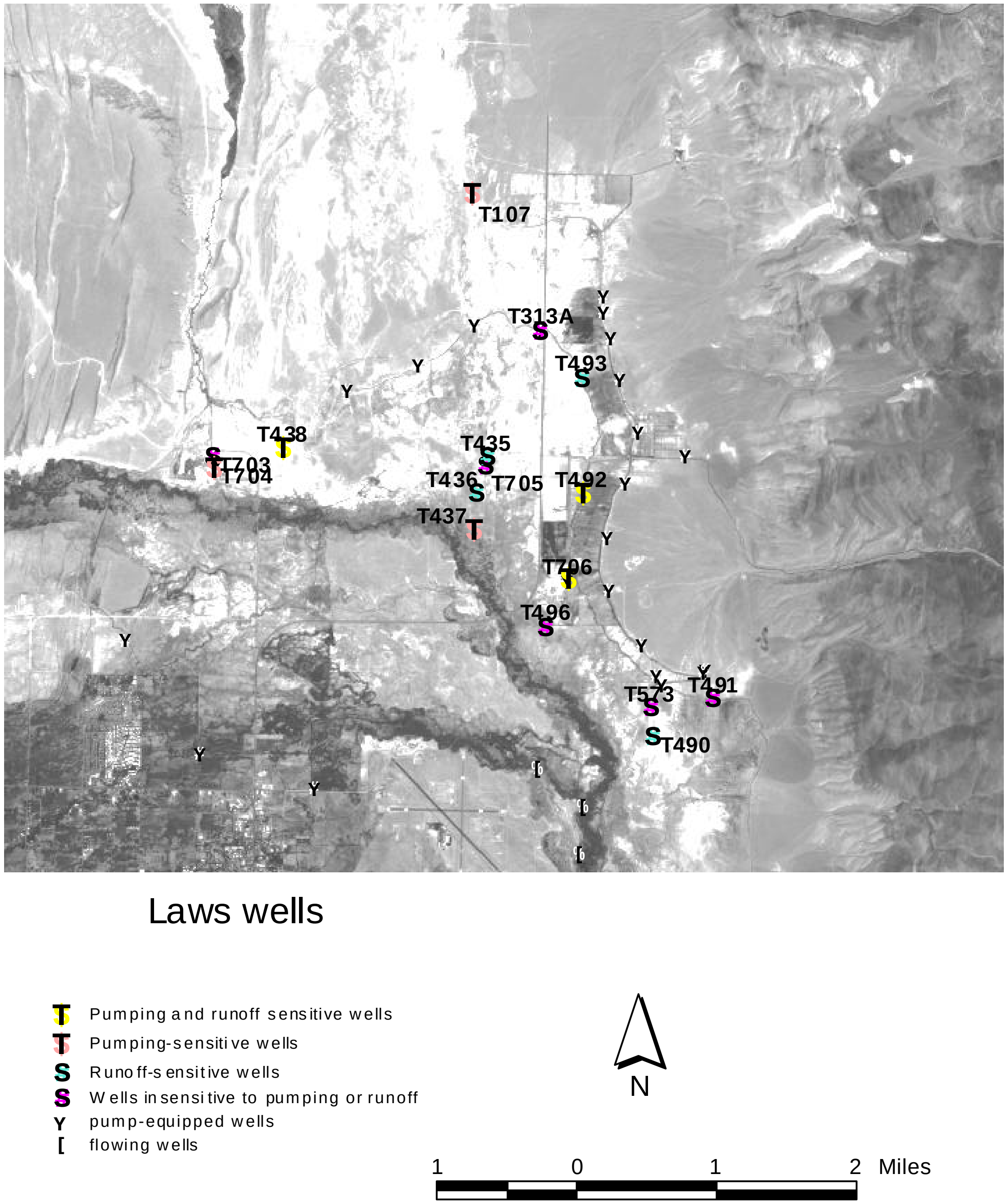


Figure 11. Laws wellfield monitoring, pump equipped, and flowing wells.

Recommendations

1. Expand the set of indicator wells used in developing annual pumping programs. Each model represents water table response at a single location; therefore, in order to have as complete as possible spatial coverage of the valley floor, the potential indicator wells listed in Table 3 should be included in water-table-based management schemes. This is desirable for two reasons: first, it provides more complete spatial coverage of the valley floor; second, it provides a larger sample of models upon which to base decisions, reducing the influence of any single anomalous well. For future management and forecast use, it will be necessary to recompute regression coefficients for indicator wells, because of the changes that were adopted in August, 1998 in LADWP's calculation of valley-wide runoff.

2. Identify areas where other modeling tools need to be developed. Ideally, the regression models should be implemented as complements to numerical groundwater flow models, rather than replacements for them. The empirical basis of regression models renders them invalid if conditions change from those prevailing during the historical record from which the model was developed. For example, the LORP will affect water table levels in the vicinity of the project. As noted in Table 3, several of the modeled wells in the Thibaut-Sawmill wellfield will probably be affected by changes in surface water management as part of the LORP, rendering regression models developed for those wells invalid. Additionally, there is a relative dearth of acceptable regression models in Taboose-Aberdeen and Thibaut-Sawmill wellfields, suggesting that that regions should be a focus for development of numerical tools. Furthermore, regression models are invalid if input variables are outside the range of the historical records, such as years of extreme runoff or drought. Though extreme events are by nature rare, they are the most critical periods with regard to making management decisions, and unfortunately are the conditions under which empirical models are likely to be least robust. Where both empirical and numerical models are valid, their predictive capabilities should be compared to determine the best tool for predicting groundwater fluctuations.

3. Management of pumping based on target depth-to-water and rotational pumping, where the water table is allowed to drop below the root zone and subsequently recover can be modeled using the Monte Carlo methods discussed above. Thresholds for depth-to-water and allowable time for desaturation of the root zone should be explored and rotational pumping scenarios analyzed. Multi-year regression modeling can provide approximate pumping yields under various management criteria, and approximate recovery rates for specified levels of pumping stress.

4. The regression models in this report are based on the assumption that the water balance of the shallow aquifer is governed by pumping and recharge. Clearly, ET is an important component of the water budget, yet ET is not directly included in the models. The inclusion of the water level as an independent variable in models 1 and 2 indirectly captures the effect of ET, but a more explicit inclusion of ET into the model might improve the predictive capability of the models. It may be possible to refine the linkage between ET and the water table by using depth-to-water (DTW) as an independent variable. DTW cannot be inserted directly into models 1 and 2, because DTW and h_0 are linearly related, but an algabraic transformation of DTW, such as $1/DTW$ or DTW^2 might provide a better accounting of ET in the models. However, introducing additional variables into the regression models should be made cautiously, recognizing the necessity for timely data or forecasts.

References

Danskin, W. R., Preliminary evaluation of the hydrogeologic system in Owens Valley, California, USGS Water-Resources Investigations Report 88-4003, 1988.

Danskin, W. R., Evaluation of the hydrologic system and selected water-management alternatives in the Owens Valley, California, USGS Water Supply Paper 2370-H, in press.

Haan, C. T., Statistical Methods in Hydrology, Iowa State Univ. Press, 1977.

Haggerty, D. J. and K. Lippert, Rising Ground Water – Problem or resource?, Ground Water, 20(2), 217-223, 1982.

Hirsh, R. M., D. R. Helsel, T. A. Cohn, and E. J. Gilroy, Statistical analysis of hydrologic data, in Handbook of Hydrology, D. R. Maidment ed., McGraw-Hill, 1992.

Hodgson, D. I., The use of multiple linear regression in simulating ground-water level responses, Ground Water, 16(4), 249-253, 1978.

Holder, R. L., Multiple Regression in Hydrology, Institute of Hydrology, 1985.

Hollet, K. J., W. R. Danskin, W. F. McCaffery, and C. L. Walti, Geology and water resources of Owens Valley, California, USGS Water-Supply Paper 2370, 1991.

Hutchison, W. R., Linear regression analysis of Owens Valley pumping April 1972 – March 1985, Inyo County Water Department Report 86-1, 1986.

Jackson, R., Water level predicting multiple linear regression models developed for shallow groundwater observation wells in the Bishop well field in Owens Valley, California, Report 96-2 (draft), Inyo Co. Water Dept., 1996.

Kufs, C. T., Statistical modeling of hydrogeologic data – Part I: Regression and ANOVA models, Ground Water Monitoring Review, 12(2), 120-130, 1992.

Press, W. H., S. A. Teulolsky, W. T. Vetterling, and B. P. Flannery, Numerical Recipes in C, Cambridge, 1992.

Williams, P. B., Changes in the Owens Valley shallow groundwater levels from 1970-1978, prepared for the Inyo Co. Board of Supervisors, 1978.

Woodward-Clyde Consultants, Multiple Regression Model Development, Report prepared for Inyo Co. Water Dept., Ref. No. 95A130, 1995.

Woodward-Clyde Consultants, Alternative Monte Carlo analyses of well 419T – Taboose-Aberdeen wellfield, Report prepared for Inyo Co. Water Dept., 1997.

Zaltsberg, E., Methods of forecasting and mapping of ground-water tables in the USSR, Ground Water, 20(6), 675-679, 1982.

Appendix 1: Regression coefficients for Owens Valley shallow monitoring wells.

Standard errors are in feet. Tables are sorted by Multiple-R. Intercepts are not included in these tables because the are not meaningful for assessing model performance. These regression coefficients are based on valley-wide runoff totals from LADWP's Totals and Means Report received by the Inyo County Water Dept. on January 11, 1994. The calculation of valley-wide runoff has since been modified, and these regression coefficients are not compatible with valley-wide runoff totals produced after 1998.