IMPROVED PREDICTION OF SALT LOADS AND CONCENTRATIONS IN STREAMS USING AUTOMATED EC SENSORS

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Abstract
The hourly measurement outputs of selected EC sensors, in Queensland streams, have been modelled in terms of both instantaneous and antecedent flow conditions. The six sites are at gauging stations with 6 to 9 years of almost continuous flow and EC data. Three stations are located in a large inland catchment with ephemeral streams, and three are in coastal catchments. The assessment of this automated data assumes that instream EC is the cumulative result of past and present hydrological processes, which are considered sequentially. The final EC-Hydrology model improves parameter correlation, particularly for ephemeral streams. These results indicate that the major processes relating to variability are at least partially accounted for. The EC-hydrology model provides a range of values for EC that are more representative of a particular site over time. This preliminary assessment indicates the method can improve the prediction of loads and salt concentrations and enable a more realistic setting of salinity targets.

Additional Keywords: salinity, EC sensors, catchment management, water quality

Introduction
Concern about land and stream salinity is widespread and successful management requires salinity target setting. It is therefore essential that the nature of salt processes and the effectiveness of remediation be known as accurately as possible. An EC/flow relationship needs to be determined for the calculation of salt loads in streams, as well as for trend estimation and predictive salinity models. A limitation, however, is that no matter how the relationship is estimated, it seldom accounts for the majority of EC variability, particularly in large, complex catchments (Jolly *et al.* 2001). Predictable sources of additional variability are serial correlation resulting from antecedent weather conditions Morton (1997), or changes during periods of no flow. The hysteresis between rising and falling stages may also be significant. Because of the high degree of scatter in most EC/flow plots, the choice of an algorithm to represent the relationship must be made subjectively, typically on the basis of the most dominant process, however, correlation usually remains poor.

It is difficult to assess the full impact of catchment hydrology on EC at a site with the small sets of manually collected data that are usually available. In response to this, the Queensland Department of Natural Resources, Mines and Energy (NRM&E) has been installing EC sensors since 1993 as part of its ambient monitoring program; there are now approximately 150 in operation (Clarke 1998). The sensors can reflect the full variability of EC over all stages of the hydrograph, and provide enough data to incorporate antecedent flow conditions to expand the EC-hydrology model.

Materials and Methods
Assessment methods used to process EC sensor records must have the capacity to handle a large volume of data which is typically over 50,000 hourly readings with accompanying flow measurements. Most previous approaches have relied on summary statistics, or the selection of representative values as in Hirst (1992). For this current study, a methodology has been developed which is largely automated, and assumes that the instream EC is the cumulative result of several processes, which are modelled sequentially.

Stream Sites
The data examined are the hourly outputs of six EC sensors with records of from 6 to 9 years with no significant gaps. Three are located in the, middle and lower reaches and a tributary of a large, dry inland catchment; the remaining three are in medium sized coastal catchments, which have more continuous flow. The sites were chosen on the basis of adequacy of the data, and the need to assess the method on a wide a set of conditions. All the gauging stations are within subtropical to tropical climates, with highly variable summer rainfall. The headwater relief is moderate, and alluvium of variable extent is present at the sensor sites. The characteristics of each catchment are summarised in Table 1. To demonstrate the method, data from the inland site on the Condamine River at Chinchilla is examined.

Table 1. Summary of stream gauges with EC sensors installed.

Stream	Catchment Area Km^3	Rainfall mm	Annual Flow Megalitres	Start EC	Comments
O'Connell R GS 124001	363	1400-2000	124,000	1994	Small, moist, lightly developed coastal catchment .
Mary R GS 138014	6845	1000-1400	807,000	1993	Permanent stream in hilly coastal catchment. Moderate development
Gregory R GS 912105	11489	300-800	521,000	1995	Permanent stream in tropical savannah. Limited development
Hogson Ck GS 422352	560	500-700	13,000	1993	Highly developed subcatchment in inland basin. Saline sediments, weathered basalt.
Condamine R GS 422308	19190	500-800	249,000	1995	Mature floodplain in inland catchment, downstream of towns and irrigation
Culgoa R GS 422204	79330	300-500	222,000	1996	Large inland catchment, stream entering alluvial fan. Dam, irrigation upstream

Methodology

The EC-Hydrology relationship has been treated in three stages: (a) definition of a median instantaneous flow; (b) incorporation of an antecedent hydrology correction; and (c) a correction for EC changes during no-flow periods, if these are significant.

The Statistical Methodology used to develop the EC/instantaneous flow initially subtracts each flow from the previous value to identify rising and falling stages. All EC data are then categorized into flow percentiles, and rising and falling stages are each sorted into percentile classes represented by their median EC. Discharge for each stage/percentile is represented by the geometric mean of the flow range. These reduced data sets are modelled to determine the EC/Flow relationship.

A number of algorithms are used to model EC against Instantaneous flow, depending on the process assumed to control the relationship. As most of these processes are nonlinear, they cannot be modelled by simple regression, and various methods have been applied. For a dilution driven system, Harned *et al.* (1981) and Hirsch *et al.* (1982) used an exponential algorithm; alternatively, a quadratic relationship based on logs of flow and parameter concentration has been demonstrated by Yu and Neil (1993). This relationship produces a maximum salinity at intermediate rather than minimum flows, allowing for a more complex EC/Flow interaction. Other approaches involve a smoothing procedure such as LOWESS (Cleveland 1979), or by removal of flow-weighted means. However, Thorburn *et al.* (1992) proposed an algorithm that is suitable for streams running through alluvial valleys where ground and surface water interact. This algorithm has been widely used in previous studies, (e.g. QDPI 1994), and is adopted here. The algorithm produces a Z-shaped curve that is asymptotic to assumed baseflow as flow approaches zero. The curve also approaches the salinity of overland flow at high flow exceedences. This algorithm is:

$$EC = \frac{K1 - K2}{1 + K3Q^{K4}} + K2$$

where K1 is the assumed EC of baseflow, K2 is the lowest EC expected in runoff, Q is the discharge, and K3 and K4 are constants relating to curvature. Rising and falling stage data were modelled separately as well as combined, and the model that best represented the whole dataset was selected. Fig.1 shows the dataset, including manual samples, compared to the model; it is evident that although the general trend of the relationship has been captured, the variability is too great to consider the model as a predictor of concentration. Fig. 1 also indicates that the higher concentrations are censored as flow reaches zero. Fig. 2 demonstrates the results of the model plotted against time.

Corrections were next developed for antecedent flow history. Three time periods were investigated: 100 hours for approximately weekly flow history, 1,000 hours for a monthly trend, and 10,000 hours for annual effects. Cumulative sums of flow for these periods are added to datafile, and these are transformed to logs to account for the assumed skewed distribution. The data are then divided into 60 sets of around 1000 records each, with sequential samples assigned to alternate sets. The residuals from the instantaneous flow model in each set were linearly correlated with logs of the cumulative flow sums. The final algorithm took the form:

$$RsidualEC2 = K5 + K6 \times Q_{100} + K7xQ_{1,000} + K8 \times Q_{10,000}$$

Where RsidualEC2 is the residual ECs remaining after the no-flow correction has been applied, Q10,000 is the log of the integral of the past 10,000 hours of flow, Q1000 is the log of the integral of the past 1,000 hours of flow, and Q100 is the log of the integral of the past 100 hours of flow. This gives a weighting to more recent conditions.

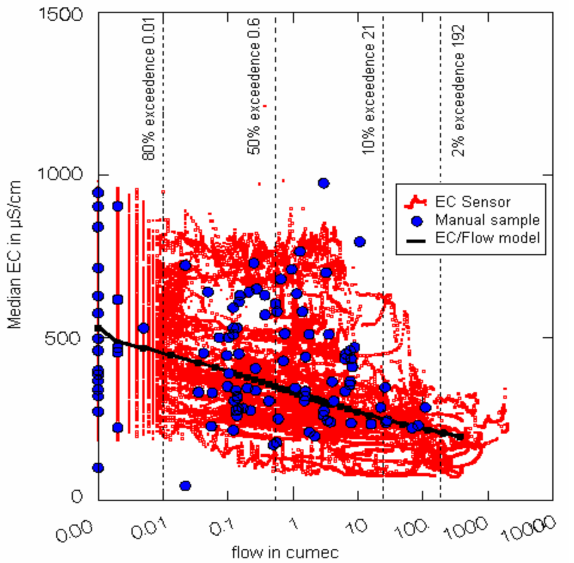

Figure 1. Flow/EC relationship modelled for instantaneous flow on Condamine River

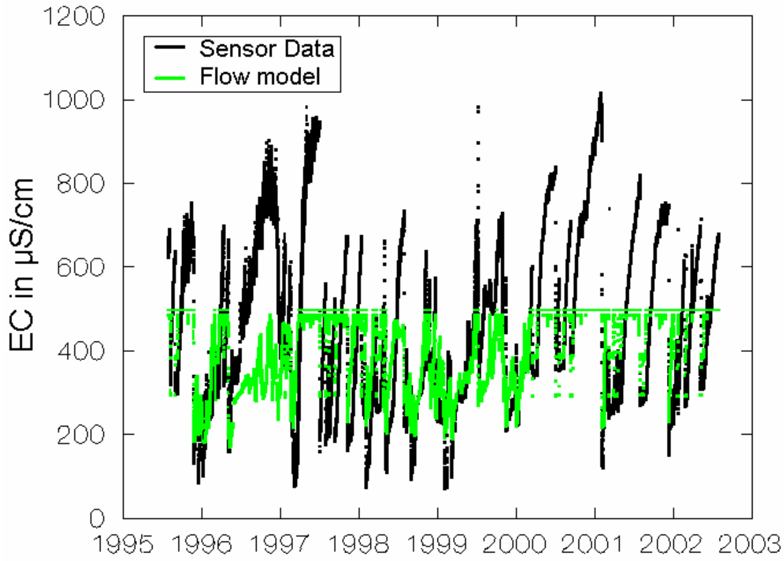

Figure 2. EC Sensor data compared with instantaneous flow model over time. No flows are a constant.

A no-flow correction was then developed for the residuals of the antecedent model, based on number of hours since flow ceased. Three prolonged no flow periods were examined, and in each case the EC appeared to follow a quadratic rise from the level at the end of flow, but at different rates for individual dry spells. It was then decided to use the most representative quadratic path to develop the correction as follows. ECs from periods of greater than 100 hours of no-flow are assigned to individual sets. Each set is modelled quadratically, and the results compared by observation to select the best model to represent the no-flow trend overall, the constant being ignored. The correction for no-flow is therefore a quadratic function, which reduces to zero during continuous flow:

$$RsidualEC3 = K9 \times hours + K10 \times hours^2 .$$

Results and Discussion

The final EC-hydrology model for the EC sensor at Gauging Station 422308 on the Condamine River at Chinchilla is shown on Fig. 3, and the distribution of final residuals on Fig .5. The multiple algorithm for the model is:

$$EC = \left(\frac{589 - 106}{1 + 1.14 \times Q^{0.23}} - 431 \right) + \left(19.7 \times Q_{100} - 91.2 \times Q_{1,000} + 176 \times Q_{10,000} \right) + \left(0.103 \times hours + 0.0001 \times hours^2 \right)$$

A brief summary of results for each site is given in Table 2. The same methodology was used throughout the investigation so that the response of stream EC to flow could be examined equivalently under a range of hydrological environments by comparing the constants produced by the model. For this reason, the algorithms used were those that produced the best overall results, rather than being optimised for a particular site.

Table 2. Summary of results of EC/hydrology modelling for each site.

Stream	Comments
O'Connell R	Strong EC/flow relationship. Antecedent and no-flow models accounted for short dry spells
Mary R	Relatively high EC variability at most stages of flow. Model was improved for higher ECs by incorporating antecedent conditions.
Riversleigh Ck	Highly seasonal flow accompanied by strong EC fluctuations. Model of limited value, but may have defined an EC trend unrelated to short-term hydrology.
Hogson Ck	Model difficult to define, due to very high and fluctuating ECs (about 100 – 3000 µS/cm). Prediction of high ECs improved by incorporating antecedent and no-flow corrections.
Condamine R	As demonstrated, model satisfactory, and improved by antecedent and no-flow corrections
Balonne R	Results similar to Condamine, which is higher in the catchment, but model less predictive of high ECs. May be due to greater flow regulation and breakup of stream into braided channels.

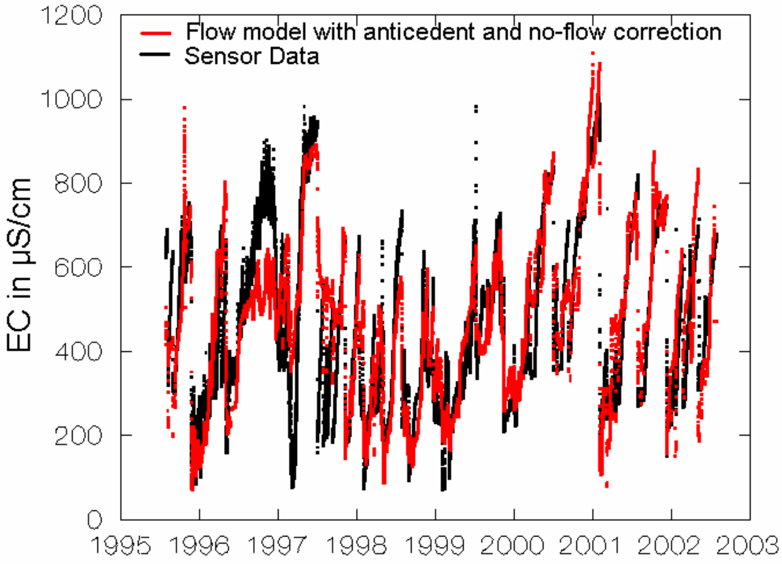

Figure 3. EC modeled by flow, antecedent hydrology, and time since flow ceased.

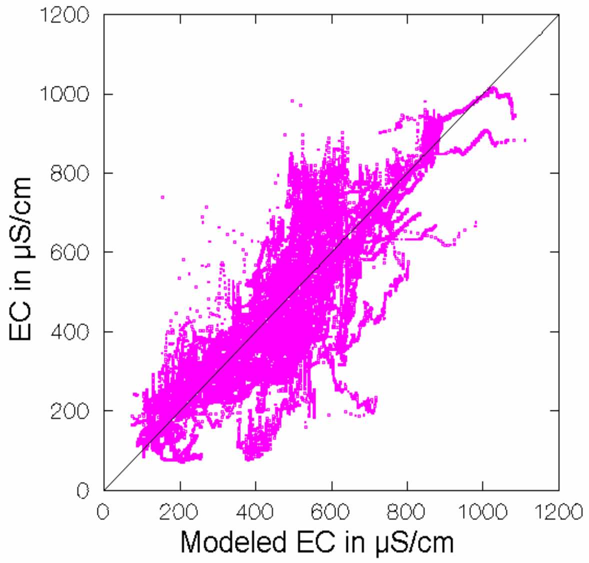

Figure 4. Distribution of residuals in final model, showing a reasonable fit at flows and dry periods

Figs 1 and 2 indicate that the Thorburn algorithm performs well in estimating EC/ instantaneous flow under high flow conditions, the most significant for mass transport. Results for the Gregory and Mary also show it to be generally applicable to permanently streams. More sites are needed to define the relative importance of antecedent conditions on residual EC variability, but some trends are evident. The annual effect is generally dominant, and weekly and annual correlations are positive. The monthly correlation is negative, and its influence is greater, particularly in relation to the annual effect, as catchment size increases or mean annual flow decreases. Baseflow EC is usually lower in larger catchments, where the EC is also slower to change during no-flow periods.

Conclusions

Despite the generalized methodology used, the EC/flow relationship is significantly improved at most of the six sites by including corrections for antecedent hydrology. Fig 3 confirms that the EC can now be defined for all conditions in this large, ephemeral catchment, and Fig. 4 indicates a reasonably narrow and even distribution of remaining residuals. The algorithms applied could only by developed through the use of a large, continuous dataset as collected at gauging stations equipped with automated EC sensors. This greater detail of parameter relationship is needed to define processes in ephemeral catchments; however, further work is required to develop and refine mathematical models for broader application to catchments of variable character.

References

Clarke R. (1998). Report on assessment of trends in surface water conductivity in Queensland. Water Quality Group, Department of Natural Resources and Mines, Queensland Australia.

Cleveland, W.S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association*, 74, 829-836.

Harned, D.A., Daniel, C.C. and Crawford, J.K. (1981). Methods of discharge compensation as an aid to the evaluation of water quality trends. *Water Resources Research* 17(5), 1389-1400.

Harvey, F.J., Buchan, A.J.C., and Henderson, R. (2000). Protocols for in-stream continuous electrical conductivity data. *Australian Journal of Water Resources* 4(2), 161-167.

Hirsch, R.M., Slack, J.R. and Smith, R.A. (1982). Techniques of trend analysis for monthly water quality data. *Water Resources Research* 18(1), 107-121.

Hirst, D. (1992). A new technique for the analysis of continuously monitored water quality data. *Journal of Hydrology* 134, 95-102.

Jolly, I.D., Williamson, D.R., Gilfedder, M., Walker, G.R., Morton, R., Robinson, G., Jones, H., Zhang, L., Dowling, T., Dyce, P., Nathan, R., Nandakumar, Clarke, R., and McNeill, V. (2001). Historical stream salinity trends and catchment salt balances in the Murray-Darling Basin, Australia. *Marine and Freshwater Research* 52, 53-63.

Morton, R. (1997). Semi-parametric models for trends in stream salinity., CSIRO, Canberra, A.C.T, Australia.

NRM. (2000). Field calibration of conductivity probes. Queensland Department of Naural Resources and Mines, Water Resource Allocation and Management: Work Practice (HSFI 5.08) Water Monitoring.

QDPI. (1994). Queensland water quality atlas. Queensland Department of Primary Industries, Water Resources Division, Brisbane, Qld, Australia.

Thorburn, P., Shaw, R., and Gordon, I. (1992). Modelling Salt Transport in the Landscape. In 'Modelling Chemical Transport in Soils'. (Eds H. Gladiri and C.W. Rose) p180 - 189 Senir Publisher

Yu, B. and Neil, D.T. (1993). Salinity trend of the Williams River, Western Australia. *Journal of the Royal Society of Western Australia* 76, 71-76.