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Status and trends of soil salinity at different scales: the case for the irrigated cotton growing region of eastern Australia

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Abstract

This paper reports on how prior information was used as a source of data for sampling schemes as well as a foundation for further salinity studies at different scales. The results at each of the scale levels are useful to the degree of sampling intensity at which the information was obtained. While the regional study revealed the salinity pattern is closely associated with climatic trend, the pattern of salinity at the county scale is less well-defined. The salinity information at the field scale revealed high saline areas coinciding with an abandoned creek channel. The salinisation process at this scale is probably due to deposition of soluble salts that have been flushed from the upper reaches of an abandoned creek. There is preponderance of saline subsoil layers in and around Mungindi which needs further investigation. Visualisation of information transfer through the scale continuum, as demonstrated by this study, is presented and discussed.

Introduction

Field survey results are routinely applied at the farm scale by Australia's Landcare Groups [3]. These Groups and many government agencies have also been pro-active in trying to identify environmental issues at the catchment scale, with further work carried out at more detailed scales right down to the plot level. Due to high cost of getting accurate and quantitative information, much is relied upon readily acquired data that are mostly descriptive and qualitative. There is also no formal documentation for reliable, repeatable salinity assessment and spatial and temporal transfer of information through the scale continuum. This paper is aimed at resolving these problems for the irrigated cotton growing region of eastern Australia. The paper focuses on the acquisition of quantitative information on soil salinity with the purpose of determining broad processes of salinisation in the region. For this, two questions need to be answered. The first is whether we can use existing information and a variety of statistical techniques to efficiently carry out field surveys that would provide economic, soil information of known quality at a variety of scales. Secondly, what is the value of soil information at various spatial scale in the assessment and monitoring of indicators of soil salinisation in the region? The focus therefore is on how we can model and identify high saline and potentially saline areas in the region.

Model specification

Physical settings as the bases for model assumption

The study region is characterised by regular patterns of climate, geomorphology and geology producing similar patterns of soil variation – varying in a similar manner from east to west [8]. This means that existing information on soil in any part of the plains can be used for sampling design and extrapolation onto the other parts. Our primary interest therefore is to utilise the only existing quantitative soil information from a previous work [8]. The work involved a soil inventory covering the Edgeroi 1:50,000 Topographic Map Sheet. The Edgeroi County is located in the lower Namoi valley, just north of Narrabri (Figure 1). The soil data at the County scale was used in designing a cost-effective sampling scheme to identify high saline and potentially saline areas at the catchment (regional) scale, and also to focus on a smaller saline areas within the County at a finer scale.

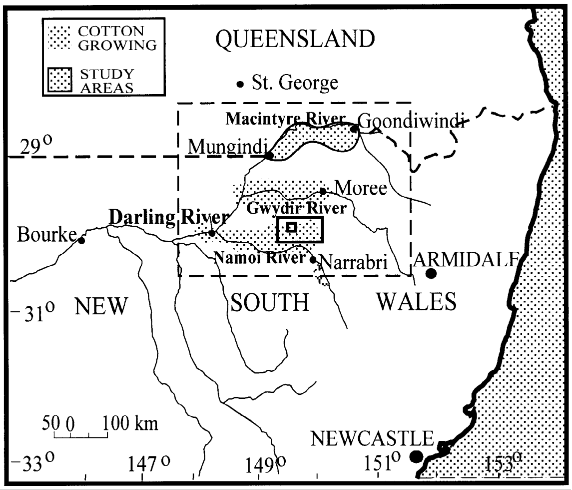

Figure 1. Location of the study region

The model

Our basic model is based on the assumption of similar patterns of soil variation, which is supported by the physical evidence of similarity of physiography throughout the plains. The next step was to develop a spatial model common to all the scales that could predict the value of our target variable (i.e.; salinity measured at a given depth) at unsampled locations. The model in consideration is in the form:

$$E[z(x)] = \mu \tag{1}$$

where E[z(x)] is the expected value of our target variable; the general model of expectation is the value of our target variables are assumed to be the population mean (μ). It is also assumed that μ does not depend on the position x. In reality, we know soil varies from one region to another therefore equation (1) could be modified as:

$$z(x) = \mu_v + \alpha_v \tag{2}$$

where μ_v is the mean value within region v; α_v is the spatially dependent residual from the mean (by implication α_v = ϵ(x) + ϵ'(x); where ϵ(x) is the spatially dependent component and ϵ'(x) represents the uncertainty).

The model concept is based on the theory of regionalised variables [7] which is well known in the soil science community. The model aim is to predict the values of our target variable at unvisited locations from measurements made in the neighbourhood, while minimising the component ϵ'(x) in equation (2). Equation (2) leads to [7]

$$\begin{aligned} &\mathrm{var}[\alpha(x) - \alpha(x+h)] = \\ &E[\alpha(x) - \alpha(x+h)^2] = 2\gamma(h) \end{aligned} \tag{3}$$

where h is the lag or the separating distance between each pair of observations; γ(h) is the variance of the paired observations at this lag (h). Equation (3) describes the condition termed quasi-stationarity whereby the variance of the differences is constant within the region of consideration only [13]. The estimate of γ(h), usually referred to as semi-variance, can be obtained by:

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (z(x_i) - z(x_j))^2 \tag{4}$$

where N(h) is the number of pairs. The plot of the experimental or calculated semi-variances against the lag is termed as the variogram. The experimental variogram can be modelled by a number of "safe" functions, the most popular of which is the spherical function. The variogram parameters resulting from the model are used for kriging, a best linear unbiased estimator (BLUE). Since our spatial model is based on the quasi-stationarity of variance, ordinary kriging [5] is the appropriate interpolation technique to be used.

Upscaling (regional – lower Macintyre)

Percent clay content at 0.30–0.40 m depth for the Edgeroi 1:50,000 map area [8] was selected as the primary variable for our sampling design at the regional scale. We started by fitting a spherical model (γ(h) =109.25 + 0.231h (km) up to the sill) to the experimental variogram from which we derived sample observation density and the kriging error for the primary variable using the resulting variogram parameters. Figure 2 shows the relationship between the density of sampling and kriging error for the % clay. Up to a certain level, decreasing the prediction error leads to improved accuracy of interpolated soil information as the sampling intensity increases. This is similar to results reported elsewhere [2]. Note that the relatively large minimum kriging error of about 10.5 (% clay) is due to a large nugget effect of the variogram used in the computation. The overall picture presented by Figure 2 is that accuracy of soil information improves with increasing density of observations that generate the information, and this could only be to a degree determined by the accuracy of the prior information used for the analysis.

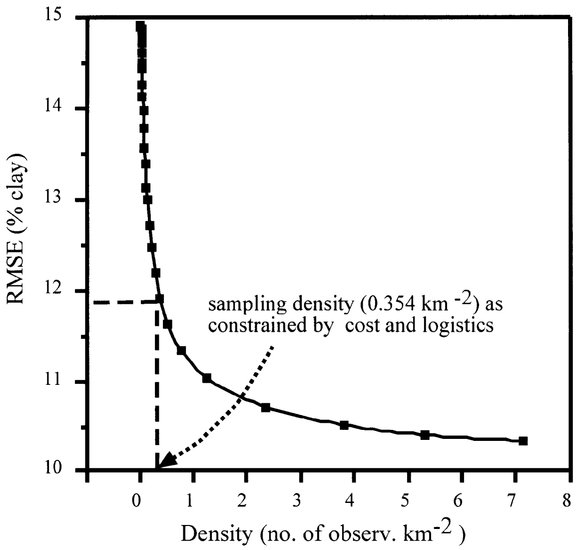

Figure 2. Plot of kriging error versus sampling density

After taking into consideration the time, cost and logistic constraints, we determined the sampling density of 0.354 observations per km^2 for the lower Macintyre valley - much lower than the optimal sampling density of about 2.4 observations per km^2 (De Gruijter, pers. communication). A total of 120 sites were visited and sampled to 2.0 m depth. However, only three depths (0.10–0.20, 0.60–0.70 and 1.10–1.30 m) were used for this study.

Downscaling (Field scale – 'Auscott')

Our aim in downscaling was to determine the extent and spatial distribution of saline soil layers within the Edgeroi area termed *Boolcarrol*, which was revealed by a prior study [11]. To test the hypothesis that salt accumulation was either due to the effect of irrigated cotton production or due to a natural phenomenon, a more detailed study focusing on selected fields in the Auscott farm, was carried out.

To determine a suitable sampling strategy, several preliminary transects with sample points at 10 m interval were laid across the selected fields. Two EM38 (an electromagnetic induction instrument [12]) readings were made at each site: in the vertical mode ($EM_{0,V}$), where the instrument measures electrical conductivity (ECa) to a theoretical depth of 2.0 m; and in the horizontal mode ($EM_{0,H}$), which measures ECa to a depth of 1.0 m. The resulting ECa were used to generate variograms that are important for designing sample spacings for the detailed salinity investigation. However, the similar shape and range (ie. 0.35 km) of the resulting variograms is indicative that the instrument appears to be measuring the same phenomenon in both modes of operation. The model for $EM_{0,V}$ is in the form:

$$\begin{aligned} \gamma(h) &= 0.3 + 5.714h \quad \text{for } 0 \leq h \leq 0.35\ km \\ \gamma(h) &= 0.3 \qquad \text{for } h = 0\ km \end{aligned} \tag{5}$$

and the model for $EM_{0,H}$:

$$\begin{aligned} \gamma(h) &= 0.2 + 3.142h \quad \text{for } 0 \leq h \leq 0.35\ km \\ \gamma(h) &= 0.2 \qquad \text{for } h = 0\ km. \end{aligned} \tag{6}$$

Considering the importance of local variation at this scale level sampling interval of 0.05 km was generally used across the fields. However, it was decided to sample more intensively along the grid lines where *Boolcarrol* was observed from the Edgeroi analysis. Sampling intervals in the "suspect" areas were varied from 1 m to 25 m.

Model validation at different scale

To validate and assess performance of our prediction model at different scales, two criteria – mean error (ME) and root mean square error (RMSE) of prediction [9], were used. The ME measures the bias of prediction and should be close to zero for unbiased methods. It is defined as:

$$ME = \frac{1}{l} \sum \{z^*(s_j) - z(s_j)\} \tag{7}$$

where l is the number of test sites; $z(s_j)$ is the actual measurement of ECe at a validation site; $z^*(s_j)$ is the predicted ECe at the validation site. The RMSE is a measure of precision of prediction and should be as small as possible for precise methods. It is expressed as:

$$RMSE = \sqrt{\frac{1}{l} \sum [z^*(s_j) - z(s_j)]^2} \tag{8}$$

Results

Basic statistics and variograms at different scales

Basic statistics of ECe measured at different scales are presented in Table 1. The mean ECe at all scales

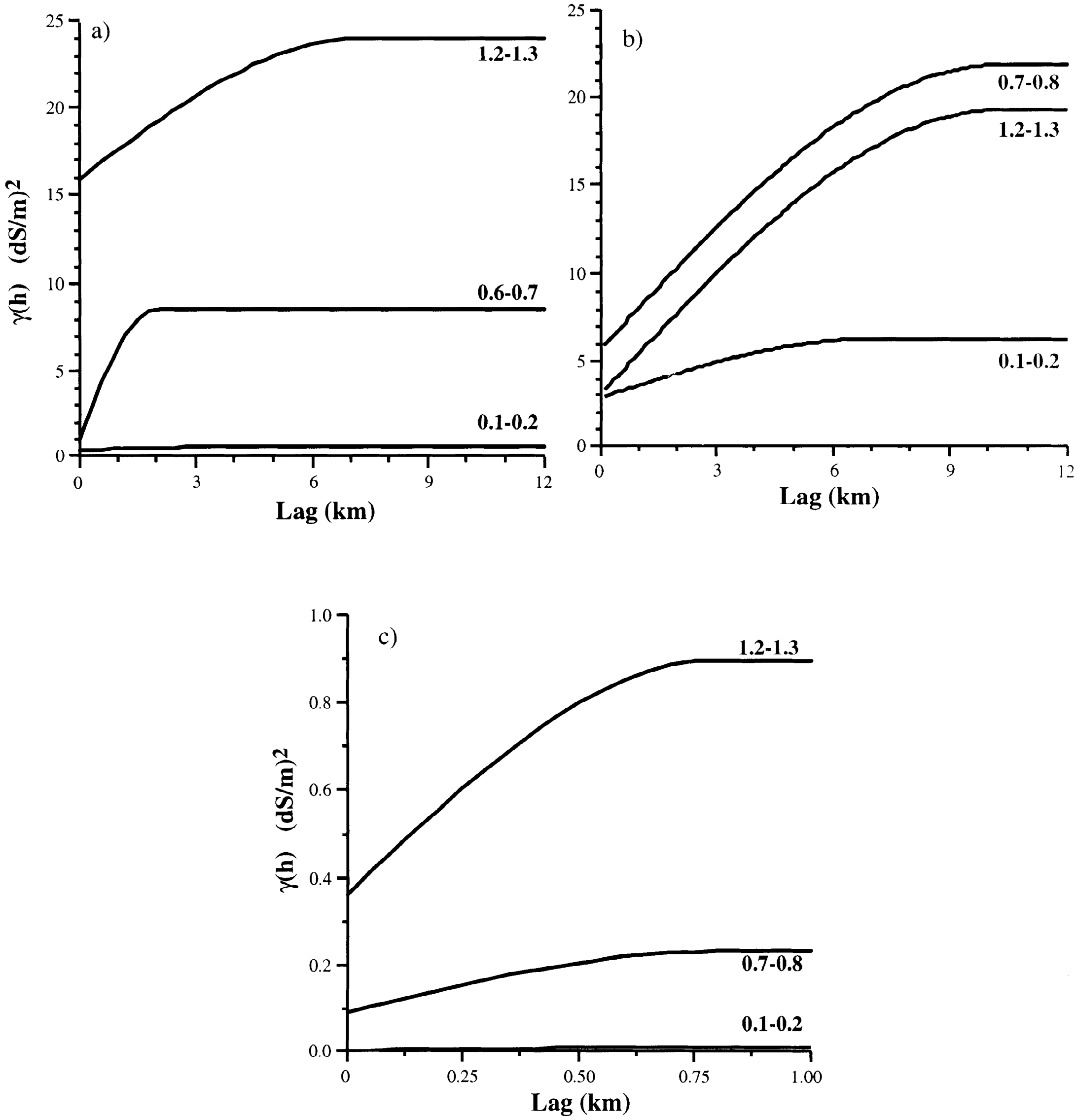

Figure 3. Variogram models (a) regional, (b) county and (c) field scale

increases with depth. These results indicate a common salinity profile which is characterised by low ECe in the topsoil, increasing dramatically at about 0.60–0.70 m forming a bulge in the 1.00–1.50 m depths [10]. There is larger variability of subsoil ECe at the regional scale than either the county or the field scales because the measured ECe at the regional scale encompasses more of the population variance than those at the county or the field levels. One may ask whether this finding is not in conflict with the basic assumption of quasi-stationarity of means and variance at all the scales. This is difficult to answer, but from the variogram models in Figure 3 our assumption of quasi-stationarity seems adequate.

We noted that the variograms are some measures of variability of an attribute. As shown in Figure 3, the variograms model for the ECe in the subsoil (1.10–1.30 m) consistently exhibit the largest spatial ranges and spatial variances followed by the upper subsoil (0.60–0.70 m) and topsoil (0.10–0.30 m). This is consistent with greater variation in salinity with increasing depth as illustrated in the statistics presented in Table 1. It is also apparent that owing to the greater intensity of sampling at the Auscott farm than the smaller

Table 1. Basic statistics of ECe at different scales; note that R = Regional (Macintyre), C = County (Edgeroi) and F = Field ('Auscott')

	Scale	n	Mean (dS m^{-1})	SD
0.10–0.20	R	119	1.038	0.708
	C	272	0.849	0.408
	F	3457	1.403	0.122
0.60–0.80	R	120	3.558	3.036
	C	306	3.210	3.758
	F	3457	2.361	0.636
1.10–1.30	R	118	6.805	5.376
	C	281	3.887	3.204
	F	3457	3.764	1.389

scale levels, the spatial ranges (Figure 3c) are greater than the sampling interval of 50 m, at approximately 0.8 km, a value that is twice the spatial range for the transects data. Similarly the Edgeroi county, sampled at 2.8 km interval, has ranges more than double the sampling interval. Remarkably, the range of the variogram model for ECe at 1.10–1.30 m is almost equal to the range exhibited by the primary variable (% clay at 0.30–0.40 m) as shown in our discussion on upscaling. Only the upper subsoil (0.60–0.80 m) has a variogram range less than the sampling interval (6 km), which is made possible by about 20 points that were located closer than the average interval.

The nugget effect, representing the uncertainty of Equation 2, also varies at different depths and scales. With the exception of Edgeroi, it generally increases with depth and increases as we upscale. In the case of 1.10–1.30 m, the nugget variance from less than 20% of the sill in the Edgeroi (county) to 68% in the lower Macintyre (regional scale). Obviously, the results of the lower Macintyre translated into sub-optimal predictions of ECe at unsampled locations and undersampled areas.

Prediction performance at different scales

As previously discussed, the validation set was used to judge the performance of the interpolation using the two indices, ME and RMSE. A clear finding, which is not surprising, is that precision was greatest (lowest RMSE) at the field scale and poorest at the regional scale (Figure 4). This can be attributed to two factors. Firstly, more intensive sampling is more precise than less intensive sampling [14]. Secondly, with increasing scale the uncertainty associated with the data increases (contributing to the nugget effect) which ultimately decreases the precision of prediction.

The case of ME as a measure of the performance of the prediction model is less obvious than for RMSE. The ME is only related to under- and over-prediction of ECe, not the precision of prediction. For instance, whereas the Macintyre ECe at 1.10–1.30 is slightly overestimated, all the other ECe measurements are slightly underestimated (Figure 4). For obvious reasons, the ME values can be misleading, as the negative and positive values tend to cancel each other, and are very sensitive to outliers.

Spatial patterns of soil salinity

Due to low variability of salinity in the topsoil (salt accumulation in the topsoil is very low at all the scales) only the results of 1.10–1.30 m layer is shown to illustrate the trend of salinity at various scales. In Figure 5a, there is a general increasing trend in salinity from east to west, with few patches of areas of high salinity, around 6–10 dSm^{-1}, south-west of Goondiwindi and just north-east of Boomi. The most salt-affected areas are found around Mungindi at the south-west corner of Figure 5a. The main cause of salinity distribution patterns in the lower Macintyre appears to be climate, with the salinity trend following patterns of rainfall and temperature [6]. In the east where the average annual rainfall is large, the soluble salts are probably flushed below 2 m depth. In the west where there is greater proportion of evaporation than rainfall, there is

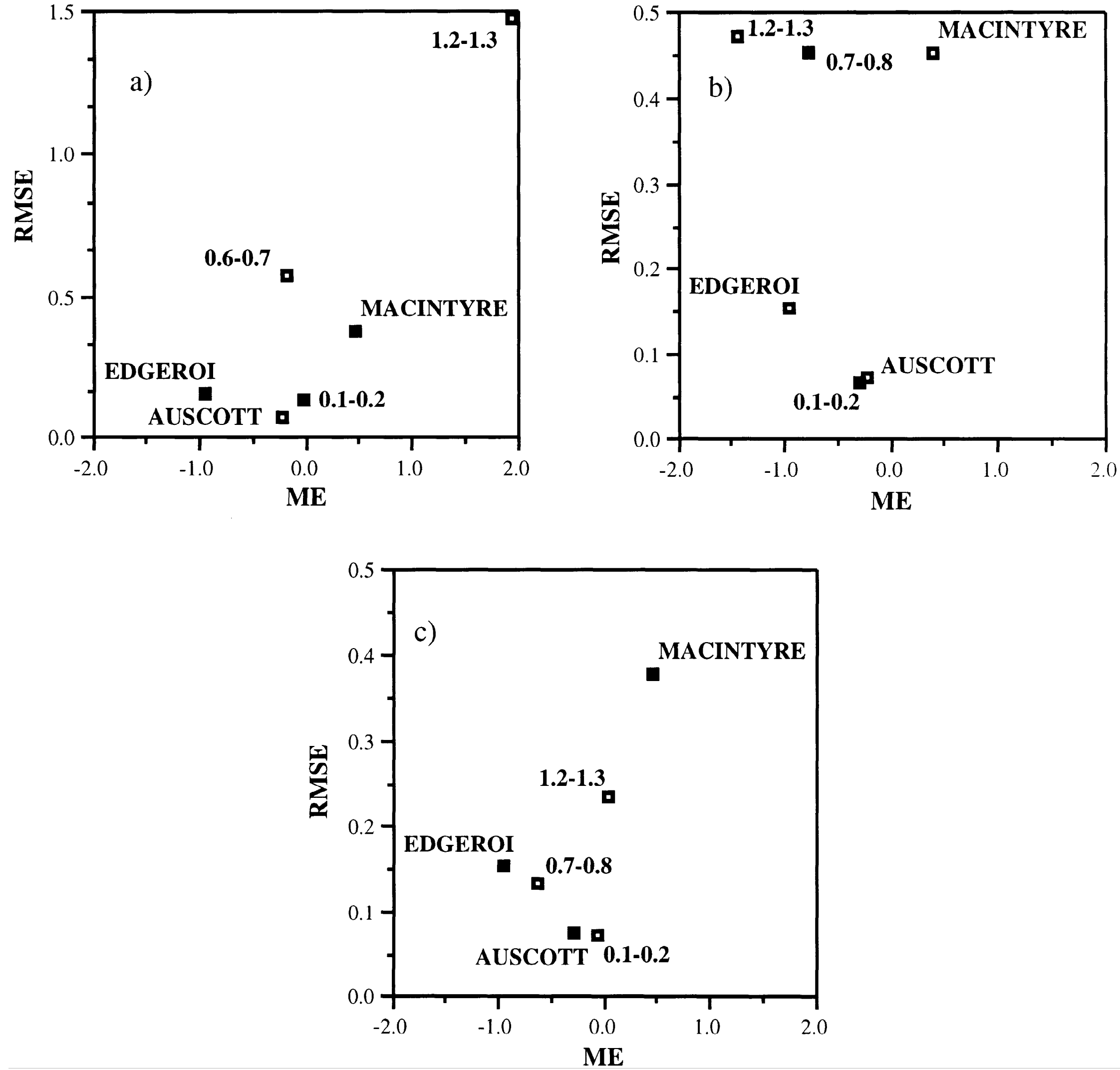

Figure 4. Plots of prediction versus bias of prediction of ECe (a) regional, (b) county and (c) field scale

upward flux of soluble salts which accumulate within 2 m depth.

The distribution of salts in the Edgeroi county indicates only a weak trend due to climatic consequence (Figure 5b). Rather, the alluvial clay plains are thought to have a greater influence in determining the distribution of salts as they generally accumulate more salts at depth [8]. As the causes of subsoil salinity are less obvious than at the regional scale, our field scale study would perhaps give a clearer picture.

At the field scale the amount of soluble salts (1.10–1.30 m depth) at Auscott is in the low to moderate range- 3.5–6.5 dS m^{-1} (Figure 5c). Although this range is lower than the critical value for cotton production (about 7 dS m^{-1}), there is an area near the Galathera Creek, running from north to south-east in Figure 5c, which is already a cause for concern to the cotton grower. There are two possible explanations for the occurrence of relatively higher salinity in this area. The probable explanation is that the salts have accumulated naturally by continual inundation of the local ephemeral Galathera Creek. The soil of the upper reaches of the Creek had been derived in situ from Pilliga Sandstone, and strongly leached of many nutrients and soluble salts. As the Creek has no natural outlet the flushed salts from the upper reaches are being deposited and now accumulate in this natural sink, areas where the creek has previously flowed. This proposition has

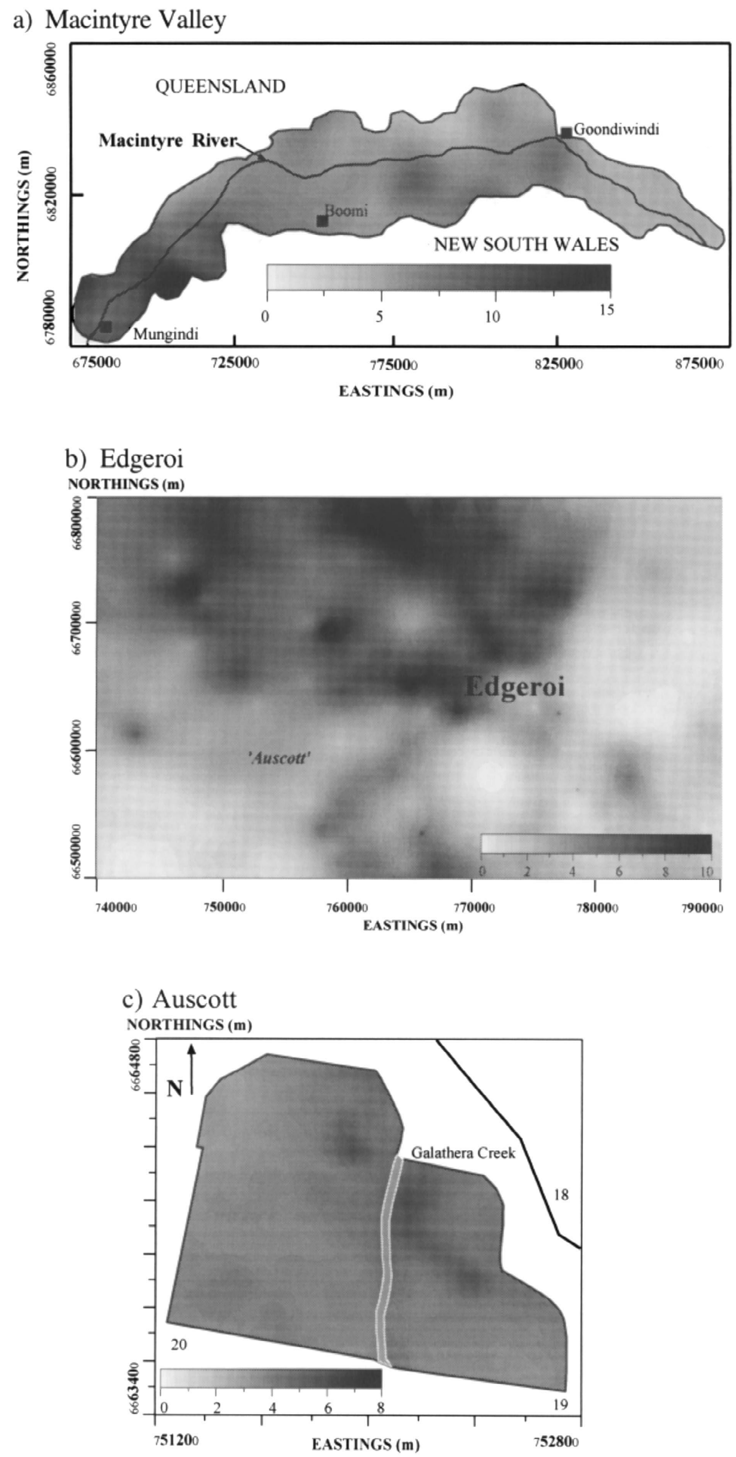

Figure 5. Interpolated ECe (dSm-1) at 1.10–1,30 m depth: (a) regional, (b) county and (c) field scale

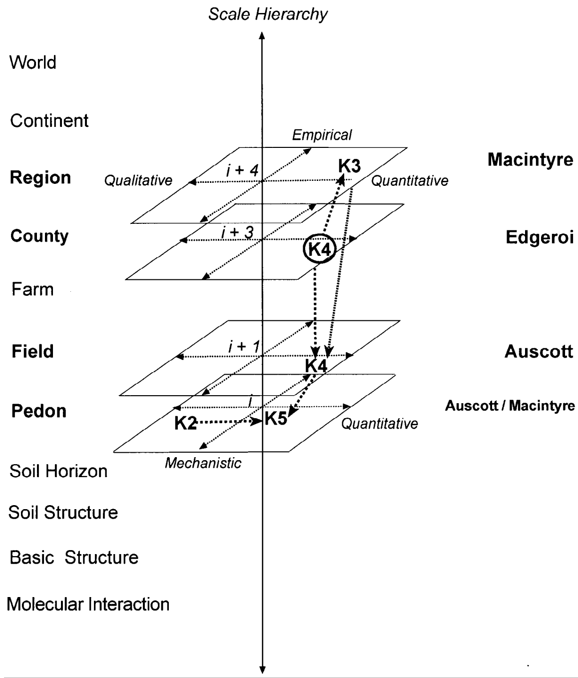

Figure 6. Model classification (after Hoosbeek and Bryant, 1992; and Bouma, 1996)

been corroborated by an old satellite photograph which shows the area of high salinity coinciding with an old channel [10]. Thus the causes of increased salinity in this area are due more to hydro-geomorphological factors than to human activities.

General discussion and conclusions

Before concluding, we discuss our approach following the model visualisation scheme of Hoosbeek and Bryant [4], with additions in accordance with Bouma [1]. The down- and upscaling procedure of this work is shown in Figure 6. We started from the level at which prior information existed- at the Edgeroi county. With medium intensity information at this scale, a sampling strategy, constrained by cost and logistics, was devised for the lower Macintyre - the regional scale. This enabled prognostication of similar salinity patterns at the county level to the regional scale, at the quantitative end of complexity. We thus upscaled to the region using a knowledge model K4 [1], which involved a complex holistic model characterised by "excellent" (quantitative) data from "carefully selected soil samples which covered a characteristic range of soil properties." At the regional scale, problem areas were unravelled for further study at the field scale - hence the proposed projection using a generalised holistic K3 model (such as SALF or SODIC) to simulate salinisation processes.

We downscaled from the county (Edgeroi) to the field scale again using a K4 model. The results at the field scale were again downscaled using a similar K4 model, combined with a K2 model (at the qualitative end) involving expert knowledge (of hydrogeomorphology), to elucidate the probable cause of salinisation at the pedon scale (Figure 6).

In conclusion, we have demonstrated how prior information can be used as a source of sampling strategy as well as a foundation for further studies at different scales. In meeting the principal problem that presage this work, we have generated quantitative information on salinity, information that has formed the baseline for future monitoring of salinisation processes in our specific study region.

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