Chapter 5.   Modelling the Utilisation of Manure and Effluent

Modelling is a method of summarising the understanding of the way a system works (EUNITA Working Group H 1997). The use of models of an agro-ecosystem has evolved from a purely academic pursuit to their practical application in land use planning, setting environmental standards (Watts & McKay 1986) and estimating the actual and potential risk of agricultural activities (Ackermann & Schlauderer 1997; Gaunt *et al.* 1997; Greenwood *et al.* 1998; Jorgensen 1997; Karm *et al.* 1995; Lewis *et al.* 1994a; Lewis *et al.* 1994b; Parsons *et al.* 1995; Shaffer 1985; Thornley & Johnson 1990; Tiscareno-Lopez *et al.* 1994; Watts & McKay 1986).

The need to balance production and environmental impacts is a common concern in all agro-ecosystems (EUNITA Working Group H 1997). This balance can be obtained through an understanding of the mechanisms and processes that can be manipulated to maximise production and minimise environmental impacts. Experiments or a model of the system under study are two alternatives that can help develop an understanding of the system. This chapter describes the Effluent and Manure Utilisation (EMU) model that was developed to contribute to the current understanding of an agro-ecosystem utilising the nutrients contained in effluent and manure.

Time, space and money are barriers to using real experiments to investigate the effects of agricultural inputs on agro-ecosystems (Attonaty *et al.* 1997; Mirschel *et al.* 1997; Myers 1995). Simulation models can be designed to encourage exploration of a system (Gaunt *et al.* 1997; Jorgensen 1997; Parsons *et al.* 1995; Stockle 1996b) and can be used to carry out virtual experiments of varying management strategies (Attonaty *et al.* 1997; Cros et al. 1997; Mahdian & Gallichand 1995; Mirschel *et al.* 1997; Stockle 1996b). These virtual experiments can be carried out at lower costs and in shorter time frames than classical experiments. Also complex environmental systems can be represented by the use of appropriate simulation models to produce meaningful and reliable simulated data (Gaunt *et al.* 1997; Marinova-Garvanska & Marinov 1997; Myers 1995; Wollin *et al.* 1982).

There are four key considerations when developing a model: the overall objectives of the modelling exercise, access to expertise, available data and available resources (Grayson & Chiew 1994). The stages of model development should incorporate these considerations and follow the sequence provided by systems research: conception, evaluation and application of the model (Gaunt *et al.* 1997).

5.1   Conceptualising the Model

There is a need for agro-ecosystem models to become holistic and developed to answer complex questions (Langensiepen 1998). Obtaining the answers to these complex questions using traditional experiments is time consuming and there is usually a limit on the number of different treatments that can be investigated simultaneously. Holistic models that consider the environment being investigated, such as the manure and utilisation area, and also the external environment, can explore the effects of different management practices. A holistic model should also deal with integrated production issues that are a combination of

agriculture, environment and socio-economic considerations (Langensiepen 1998). However, this is not a trivial exercise (Attonaty *et al.* 1997) and there is a lack of clear, readily available guidelines on appropriate modelling strategies to employ in developing simulation models of agro-ecosystems (Gaunt *et al.* 1997).

A literature review by this author (Appendix B) found some models simulate the utilisation of manure (Schmitt *et al.* 1997; Thompson *et al.* 1997), some that look at the irrigation of effluent (Hu 1995, MEDLI 1997), while others are design tools (Hu 1995, MEDLI 1997; Watts & McKay 1986, Lott 1998). Very few are focused on sustainable management of the utilisation of both manure and effluent (Lewis *et al.* 1997; Sri Ranjan *et al.* 1995), which is a requirement of this study.

Crop growth simulation models, weather generators, geographical information systems, and risk assessment economic models are now emerging as the tools able to assess the sustainability of a system (Stockle 1996b). These tools are necessary for developing a predictive ability in relation to the sustainability of an agricultural system (Syers & Craswell 1995). Given the heterogeneous nature of the systems being investigated, especially the soil system, there is a need to base these tools on a stochastic approach rather than a deterministic approach (Iskander 1981).

5.2   Study Purpose and Intended Use of the Model

One of the essential components to incorporate in the model is the ability to observe long term trends as a function of the stochastic variables that drive the system. In a stochastic system, the future is distinguished from the past through uncertainty (Hansen & Jones 1996). Therefore, models should not necessarily attempt to provide a definitive answer to the questions posed, but rather produce probabilities of the likely outcomes.

By evaluating the fate of nutrients within the utilisation area, decision-makers can observe the relative size of nutrient pools at various points in the system (Eigenberg *et al.* 1995). A systems framework can be used to provide the tool to evaluate the fate of nutrients and will further aid in the identification of gaps in the existing knowledge base and establish the direction future research should take (Eigenberg *et al.* 1995; Kruseman *et al.* 1996; Park & Seaton 1996).

An important requirement of the model developed in this study is to provide a practical tool for the evaluation of sustainability by predicting nutrient output pathways using data collected as part of a routine monitoring program (Maul & Koch 1996; Sriskandarajah & Dignam 1992). Part of evaluating sustainability is tracking changes through time, which requires a reasonable baseline dataset.

5.3   Objectives of Modelling the Utilisation Area

There are three main objectives of the modelling phase of this project. The first objective of the model is to develop an understanding of the nutrient fluxes in and surrounding an agro-ecosystem that is utilising

manure and effluent as a production input, by investigating the output pathways of N, P, Na, K, Ca and Mg (Fairweather *et al.* 1998). The model will then be used to investigate the manipulation of the various system inputs and their effects on the system outputs. The aim of the first objective is to develop a model that will provide a data analyses framework and a tool for testing hypotheses (Grayson & Chiew 1994). The second objective is to provide a relatively simple representation of the fundamental variability in the agro-ecosystem, rather than a precise representation of particular sub-components (Grayson & Chiew 1994). The final objective is to produce a robust, conceptually based model of the daily water and nutrient balance fluxes in the utilisation area (Sivapalan *et al.* 1996). The aim of these last two objectives is to be able to use the model to quantify the outputs from a system that utilises manure and effluent.

The process used to select sub-models and verify the final form of the model is as important as the data used to formulate and test the model (Gaunt *et al.* 1997). Keeping the model as simple as possible is also an important component in the development of the model, as there is not strong evidence that increasingly complex models are required to answer the many agricultural questions that abound today (Bassett 1997). The following sections outline the sub-models and the processes that are considered important for a model simulating the utilisation of manure and effluent.

5.4 Model Assumptions

The discussion of the developed model includes only elements of the production and environmental systems in the context of sustainability. The economic and social aspects of sustainability are not considered. The products of weathering (Lee & Pankhurst 1992) are also ignored and it is assumed that the tillage techniques used are those that control and create an environment for the optimum utilisation of soil organisms (Lee & Pankhurst 1992). The effects of tillage and cultivation are not incorporated into the EMU model, as the objective of the model is to investigate the effects of different timing and rates of application of manure and effluent over a long period, and this omission is not thought to be significant. That is, the cultivation practices are assumed to be constant for all the management practices investigated.

The effects of the manure additions on the moisture holding capacity of the soil are also not considered, due to a lack of data at this time. When these data become available, this function should be incorporated into the EMU model. However, its omission at this point is considered to have the effect of overestimating the runoff.

Other assumptions include the form in which P and N are added to the system and the manner in which they transfer from the adsorbed state to the soil solution. Inorganic forms of P additions are considered to stay in solution on the day of application only, and therefore can only move through the system on that day. There is no provision in the model for P to transfer back to the soil solution once it is in the adsorbed state, regardless of the total P in the soil. It is also assumed that the plant can readily utilise P when adsorbed and in solution. This approach is adopted to simplify the code, as it is believed that P is not a limiting nutrient in the crop production system at Tullimba. The maximum P sorption capacity of the soil

is also not considered in the current version of the EMU model. The cumulative effect of P in the soil is covered in the MEDLI Model (MEDLI 1997).

The only N transformation included in the EMU model is the net mineralisation of organic N to an inorganic form. In this form, N is available to the plant and is considered to remain in the soil solution. Organic N is not available to the plant and is considered to be in an adsorbed state. These assumptions are necessary to maintain simplicity in the model and still provide the tools necessary to partition each of the nutrients into the appropriate pathways of leaching, runoff and plant uptake.

5.5 Important Processes to Include in the Model

Watts and McKay (1986) investigated the mechanism for the cause of feedlot pond overflows. In some climates (e.g. Dalby and St George, Qld) overflows were correlated with floods and therefore they argued the environmental consequences of these overflows would be insignificant. Results from other sites demonstrated that "a series of chronic rainfall events" caused the pond to overflow and not a catastrophic storm event (Lott & McKay 1990; Watts & McKay 1986). Therefore, it is important to characterise the rainfall pattern of a climatic area where a system that is driven by the hydrological cycle is being investigated.

5.5.1 Climate Generation

The most important variables in the simulation model of the manure and effluent utilisation area are the hydrological variables, as these "drive" the system. The stochastic nature of these variables is captured in the EMU model using a Monte Carlo simulation. The Monte Carlo generation of rainfall and evaporation uses statistical distributions for the monthly rainfall and the number of continuous rainfall days (see Section 6.1).

Productivity levels are likely to be affected by shifting climatic conditions (Engelen et al. 1995) and the use of the stochastic rainfall variables will enable the effects of climate change on the system to be investigated (Hamer et al. 1987). There is also a great deal of variability in the inputs, changes of state and outputs in the system, most of which are driven by the climatic conditions and the uncertain and unpredictable additions to, and losses from the "as excreted" manure (Eigenberg et al. 1995). As the climate also impacts on crop growth and water uptake, and hence affects the cycling of nutrients in the soil system (Sri Ranjan et al. 1995), the generated daily weather data should have similar statistical characteristics to the actual weather data (Attonaty et al. 1997; Ndlovu 1996).

5.5.2 Crop Growth

Some crop production models reflect an out-of-date criterion of maximum production (Attonaty et al. 1997), without considering environmental impacts. The objective of the crop growth model developed in this study is to provide a realistic representation of this nutrient output pathway. Crop growth rate as a function of transpiration quantity and efficiency have been found to be robust and appropriate (Hamer et

al. 1987). Johnson (1998) used crop growth as a function of transpiration in the WaterMod model and this approach has been adopted in the construction of the EMU model.

The uptake rate of base cations and N from the soil by plant biomass is proportional to the rate of plant growth (Sverdrup *et al.* 1995) and hence transpiration. Therefore, crop growth models rely on reasonable simulations of the soil water content (Mahdian & Gallichand 1995).

5.5.3 Soil water

Transport processes in most natural sciences are described by reliable empirical relationships, for example, electrical resistivity, thermal conductivities, specific heat capacities, molecular diffusing coefficients etc. All of these coefficients are relatively uniform, however, the hydraulic conductivity of a soil changes seven orders of magnitude over the possible range of its water content (Iskander 1981) and therefore water flow in the soil-water system is complex and difficult to model (Iskander 1981).

The concentration and distribution of solutes within the soil depends on the soil's hydraulic conductivity and water-retention properties. The primary factor affecting the concentration and distribution of the solutes is the amount and quality of the percolating water. As the water can exist in a solid, liquid and gaseous state simultaneously in the soil profile, it adds to the difficulties in trying to model and predict the soil-water-plant system utilising manure and effluent (Iskander 1981).

Some mathematical formulations used in agro-ecosystem models have attempted to define soil water characteristics using algorithms over a range of complexities (e.g. GLEAMS (Leonard *et al.* 1987) and Gleams-SWAT (Reyes *et al.* 1994)). However, the simple monthly mass balance has been successful in the CENTURY model (Natural Resource Ecology Laboratory 1998). CENTURY employs a simplified monthly water budget of evaporation, transpiration, precipitation and flow of water between soil layers. This simple mass balance approach is adopted, using a daily time step, to represent the important soil-water system in the EMU model.

When a simple mass balance approach is adopted, it is important to define the soil layers. Dividing the soil into compartments corresponding to the natural soil stratification would seem appropriate, as soil horizons have similar chemical and physical properties throughout their depth (Sverdrup *et al.* 1995).

Hydrological simulations are better if the representation of the processes results in simple tools that can be structured to a particular problem (Grayson & Chiew 1994), such as an elemental water-balance bucket of finite storage (Grayson & Nathan 1993). This approach was used in the development of the soil water module described in Section 5.7.9 and includes rainfall and irrigation inputs. Water movement is downwards from gravitational forces, with upward movement of the water being possible only through evapotranspiration. In the context of the approach adopted for the EMU model, little error is introduced into the soil water balance by neglecting upward flow due to capillary action (Ritchie 1981).

5.5.4 Nutrient Fluxes

There are number of methods to model nutrient fluxes. As in the treatment of soil water, they range from simple mass balance principles that redistribute the nutrient in the profile as a function of water movement (Hamer *et al.* 1987) to the use of algorithms that are functions of dispersion, temperature, soil moisture and other variables. The method used to represent the fluxes of N, P, Na, K, Ca and Mg in the EMU model are outlined in the following sections.

5.5.5 Nitrogen and Phosphorus

Transformation of N in the soil encompasses the whole spectrum of the N cycle (Gilmour *et al.* 1977). At the field scale, the factors that control denitrification of N are the rate of nitrification, soil organic matter decomposition (Gaunt *et al.* 1997) and moisture content (Saleh *et al.* 1994). However, the rate of mineralisation is the limiting factor for all the subsequent changes (Gilmour *et al.* 1977).

A variety of models used to approximate net mineralisation of N have been developed using various relationships between mineralisation rate and temperature and mineralisation rate and soil water content, or relative available water content (Skjemstad *et al.* 1987). These relationships indicate several sources of organic N may undergo mineralisation simultaneously at different rates and models have been developed which incorporate two-pools. One pool mineralises rapidly and the other pool slowly.

There are fundamental questions about the fractions of organic matter that are labile or active and the factors that control the rates of mineralisation (Edwards *et al.* 1993). Nitrate is the biggest concern from an environmental point of view. For these reasons, only the net mineralisation of N is considered in the model developed in this study.

When organic matter is first applied, net immobilisation generally occurs to satisfy the needs of the large microbial population that arises in response to the addition of the organic material (Gilmour *et al.* 1977). This condition is only temporary and in a few days or weeks there is a net mineralisation of N (Gilmour *et al.* 1977).

A decay series is generally applied to the mineralisation of organic N (Kardos *et al.* 1977; Shaffer 1985; Sri Ranjan *et al.* 1995; Stockle 1996a). This series can be used to determine the mineral N available for plant use following a manure or effluent application. In terms of management this can be used to investigate different application rates that will maintain a constant pool of plant available N. It can also be used to assess the potential nitrate contamination of ground water (Kardos *et al.* 1977).

It is generally assumed that the many P adsorption sites in most soils will mean that adverse ground water effects are not likely to develop due to the immobility of P and leaching of this nutrient will be the exception, not the rule (Geary & Gardner 1996; Klepper *et al.* 1998; Skilton *et al.* 1998). In the EMU model, the majority of the P additions are assumed to be in an adsorbed state and therefore not susceptible to leaching.

This assumption is supported by Figure 5.1, which graphs the time series of ortho-P in the ground water from all the piezometers at the Tullimba research feedlot. The time series for each piezometer follows a similar pattern and provides evidence that the fluctuations in the ortho-P in the ground water are caused by some factor not associated with the utilisation of the manure and effluent. If the P added in the manure and effluent were being leached to the ground water it would be expected that there would be pulses in the piezometers in the irrigation area that are not parallelled by pulses in the piezometers up-gradient of the feedlot. It would also be reasonable to assume that a lag of these pulses would also be apparent in the piezometers below the irrigation area. Clearly these pulses are not evident in Figure 5.1 and it can be confidently predicted that at this point in time there is minimal leaching to ground water of the P added in the manure and effluent.

5.5.6 Cations

Most of the models investigated in Appendix B are concerned with the fate of N or P. This is understandable, as the effects of these nutrients are usually obvious after a short time period (Gilmour *et al.* 1977). Only a few authors (Keeney & Wildung 1977; Stewart & Meek 1977; Sverdrup *et al.* 1995) have addressed the long term effects on the soil from the imbalance of cations or other nutrients. Na, K, Ca and Mg are the cations included in the EMU model.

In an agricultural system, leaching of salts from the root zone is considered "good practice" to prevent salt accumulation in the root zone (Beke *et al.* 1993). However, this can cause large imbalances in the cation balance and induce acidification of the soil system (MRC 1996; Sverdrup *et al.* 1995) and cause deterioration in ground water quality (Beke *et al.* 1993). If acidification is allowed to proceed to a point where the ion exchange reservoir is nearly empty, recovery of the system will be slow and the time for the ecological damage to be repaired will be in the order of centuries (Sverdrup *et al.* 1995). "Thus any policy that envisages waiting until damage is evident is bound to fail if ecosystem protection is an objective" (Sverdrup *et al.* 1995).

Sverdrup *et al.* (1995) found that excessive leaching is a significantly larger pathway for the removal of base cations from the system then tree growth. Cation exchange is recognised as one of the most important processes responsible for the removal of cations from the soil (Iskander 1981). Therefore, the development of a tool that is able to predict the management practices that are most likely to have adverse effects on the cation exchange, in the context of the utilisation of manure and effluent, would seem paramount.
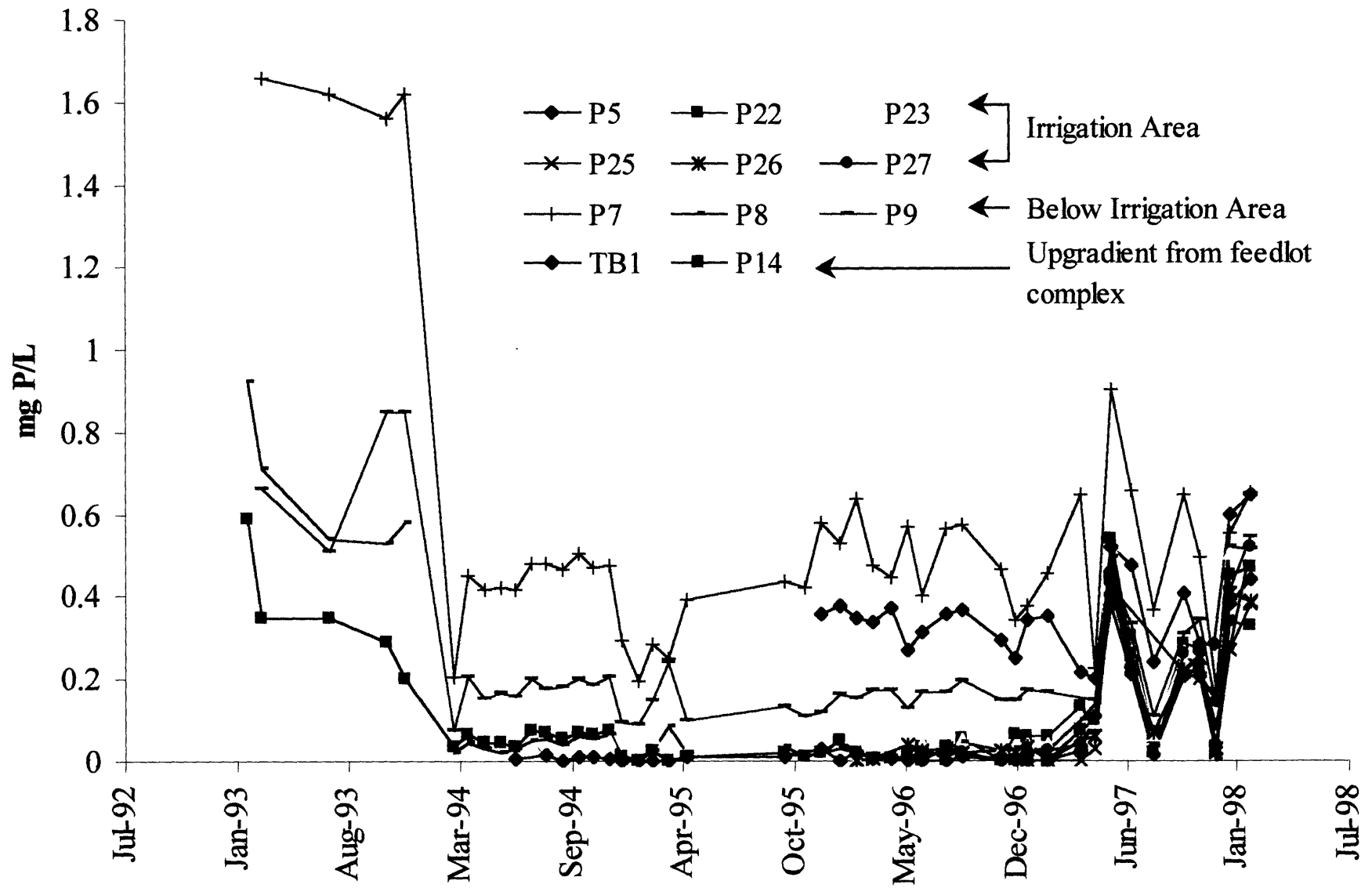
Figure 5.1 Ortho-P in Ground Water at Tullimba Feedlot

5.6 Temporal and Spatial Scales

Deciding data, parameters, spatial and time scales that are appropriate for the modelling being undertaken, and how best to evaluate the model are complex issues and are the focus of continuing research in the agro-ecosystem modelling area (Gaunt *et al.* 1997). There is significant temporal and spatial variability associated with the inputs, outputs and changes of state of an agro-ecosystem. Characterising this variability is important in evaluating the sustainability of any system and requires long series (30 or more years) of crop responses to these fluctuations (Stockle 1996b). However, degradation of an agro-ecosystem is a response to changing and environmental and socioeconomic circumstances (as opposed to an intrinsic property of a system) and therefore any predictions that are for more than 10-15 years would be in the absence of incorporating these changes (Hansen 1996).

A daily time step is used in the EMU model, as drainage is one of the key pathways for nutrient loss. Using a daily time step allows an investigation into the effects the timing of application of manure and effluent have on the long-term sustainability of the system. Using a monthly time step and a percentage of the nutrients in manure and effluent applied being lost to drainage every month would not allow these effects to be studied with any degree of reliability.

Time is conventionally thought as linear, however, a cyclical view "allows for the better evaluation of the role of positive and negative feed-back loops" (Hamblin 1991). This cyclic view incorporates the seasonal and annual variations that are evident in hydrological data. This is important in terms of assessing the equilibrium of the system (Hamblin 1991).

5.6.1 Data Requirements of the Ideal Model versus Data Reality

Data availability has been recognised as the single most important constraint to the functionality of a modelling exercise (Grayson & Chiew 1994; Gaunt *et al.* 1997). Deciding whether a computer simulation bears any relationship to reality is dependent on data availability for development and testing (Grayson & Chiew 1994). Even though there are many models available, data is generally of poor quality for environmental modelling exercises (Gaunt *et al.* 1997) and the availability of data has to be an important consideration in the development of the EMU model.

5.7 Model Description

Models should be integrated into more general software frames (Mirschel *et al.* 1997). The Monte Carlo simulation model (the EMU model) described in this section is built in the Microsoft Access environment. This is to enable data that has been stored in the database to be used as input to the EMU model with little or no manipulation. The Structured Query Language (SQL) is used to configure data for the rainfall and evaporation distributions and other queries that are accessed throughout the program.

There are several examples in the literature of models that have been built within the framework of a Microsoft Access database (Lay 1997; Lewis *et al.* 1997). Figure 5.2 is a schematic of the modules included in the EMU simulation model that has been built in the Microsoft Access environment for this study. As no model can be considered perfect, the challenge in developing the model was to select sub-models that are the least imperfect (Gaunt *et al.* 1997).

5.7.1   Data Input and Initialising Variables

There are several types of variables used in the code and several methods of assigning values. Some single variables can be changed via the user interface while others are assigned a value as a result of a "Lookup" operation. In the latter case, the tables in the database are used to look for a value, based on the value of another variable. Some of these variables are also assigned on the basis of the number of records in a particular table, for example, the number of manure applications.

Static variables initialised at the beginning of the program are the number of soil layers, the number of cations, the number of crops and their planting and harvesting dates and the mineralisation coefficients for organic N. The number of crop, manure and fertiliser applications are determined by using the Access "Dmax" function to determine the highest number that is recorded in the manure and fertiliser table and the crop cycle table, respectively.

Crop cycle and manure and fertiliser additions for the period of the simulation can be input via the interface. This information is stored in tables and additions can also be made directly to these tables. Actual crop cycles, manure additions and monitoring data can be used to evaluate the performance of the model (see Chapter 7).
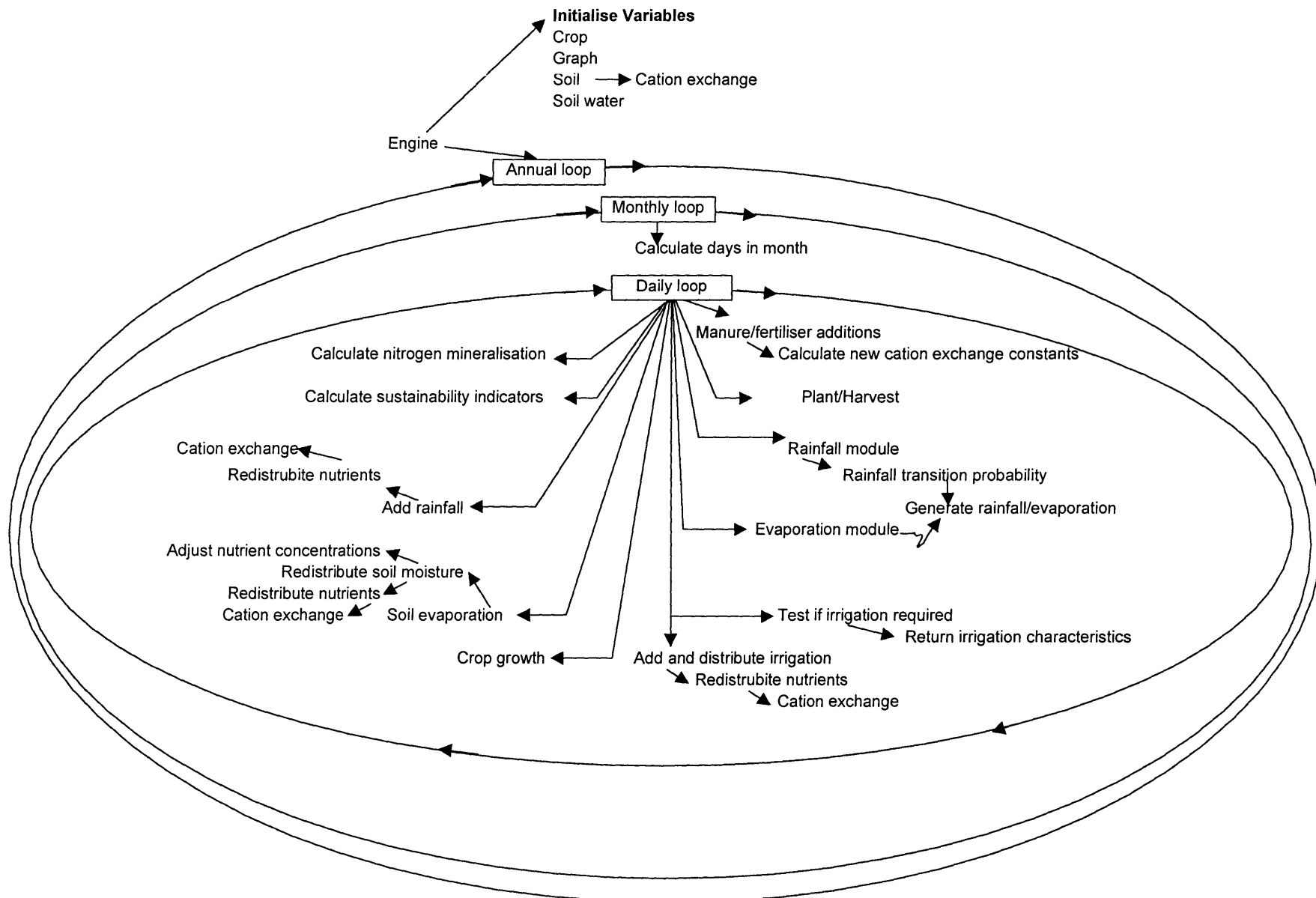
Initialise Variables
Crop
Graph
Soil ──► Cation exchange
Soil water

Engine

Annual loop

Monthly loop

Calculate days in month

Daily loop

Manure/fertiliser additions

Calculate nitrogen mineralisation

Calculate new cation exchange constants

Calculate sustainability indicators

Plant/Harvest

Cation exchange

Redistrubite nutrients

Rainfall module

Rainfall transition probability

Add rainfall

Generate rainfall/evaporation

Adjust nutrient concentrations

Evaporation module

Redistribute soil moisture

Redistribute nutrients

Cation exchange   Soil evaporation

Test if irrigation required

Return irrigation characteristics

Crop growth

Add and distribute irrigation

Redistrubite nutrients

Cation exchange

Figure 5.2. Schematic of Simulation Model

Several variables, which store a single value that can be changed as the program runs, are given an initial value (usually zero) at the beginning of the program. These are incremented as the program runs and include the number of manure and effluent applications, drainage events, runoff and rainfall events. Other single variables are included in different modules of the program and will be explained in their respective sections.

A number of one and two-dimensional arrays store values such as the soil moisture and physical characteristics and nutrient values for each soil layer. Other array variables store the gross amount of nutrients added and lost through manure and irrigation additions, drainage, runoff and plant uptake. These arrays are assigned dimensions at the beginning of the program. For example, the array to store the amount of nutrient lost to drainage is declared a one-dimension array for each nutrient. The arrays that store the nutrients in each layer are declared as two-dimensional with the number of layers and number of nutrients determining each dimension.

A user interface has been built where the user enters the number of years for a particular simulation run. There is also an option to repeat a simulation using rainfall and evaporation that have been generated in a previous run. This can be used to observe the effects of changing the timings of manure and effluent additions. Stored data collected as part of the monitoring program can also be used as a means of evaluating the performance of the EMU model.

The structure of the program incorporates a main "engine", from which all other sub routines are called. The first call is to the "initialize_crops" module. This module stores the planting and harvesting dates for each crop, which are entered through the user interface and stored in separate arrays for the day, month and year. Potential crop yield, maximum growth and water use efficiency values are entered into variables by looking up the respective tables and the user can alter these by changing the values in the tables. Crop uptake values are obtained by looking up a table that averages crop yield data for each crop type.

The next call is to the "initiliaze_soil" module. In a similar way to the plant module, the soil physical characteristics such as density and soil depth for each layer are read from the respective tables and stored in array variables. The values for the initial nutrient status of the soil are also assigned at this point. The cations are in mequiv/100gm and the N and P data are in mg/kg. Values for the adsorbed and soluble cations and organic and inorganic N and P for each layer are stored in their respective arrays and these values can be manipulated through the user interface.

The "cation_init" module is called which converts the cation dimensions to mequiv/cm^3 of bulk soil and calculates the cation exchange capacity (CEC) of the soil. The CEC is the sum of the adsorbed cations and is calculated for each layer. Control is returned to the "initiliaze_soil" module where the valency and atomic mass of each cation is looked up and used, along with the soil depth, to calculate the gross amount of each cation in the soil in kilograms.

Adsorbed and solution values for each cation (mequiv/cm^3) are passed to the "cation_exchange_constants" module. This module calculates the exchange constants for the various cations (see Frissel & Reiniger 1974), used during the program to calculate the movement between the adsorbed and solution state for each cation. The algorithms used to calculate the three exchange constants for four cations are shown in Equation 5.1 to Equation 5.3 (Frissel & Reiniger 1974).

$$X_{Na,K} = \frac{K_{sol}}{Na_{sol}} \times \frac{Na_{ads}}{K_{ads}}$$ .... **Equation 5.1**

$$X_{Ca,Mg} = \frac{Mg_{sol}}{Ca_{sol}} \times \frac{Ca_{ads}}{Mg_{ads}}$$ .... **Equation 5.2**

$$X_{Na,Ca} = \frac{Ca_{sol}}{(Na_{sol})^2} \times \frac{(Na_{ads})^2}{Ca_{ads}}$$ .... **Equation 5.3**

where

Na_{sol}, K_{sol}, Ca_{sol}, Mg_{sol} = amount of each cation in the soluble form (mequiv/cm^3),

Na_{ads}, K_{ads}, Ca_{ads}, Mg_{ads} = amount of each cation in the adsorbed form (mequiv/cm^3), and

$X_{Na,k}$, $X_{Na,Ca}$ and $X_{Ca,Mg}$ are the exchange contstants.

These exchange constants do not change unless manure is added to the system. If the soluble or adsorbed component of some cations is depleted to zero, an error will be returned in the calculation to obtain the exchange constants. To prevent this error from occurring, an "IF...THEN" statement is used to assign a small number to the soluble and adsorbed cations, if they have zero values.

The control is once again returned to the "initiliaze_soil" module where the gross values of organic and inorganic N and P in the adsorbed and solution phases are calculated from the input initial concentrations, soil density and depth for each layer. The initial carbon and aluminium values are also stored but are not used in any of the subsequent modules. They have been included at this point so modules can be added to the program at a later date, without the need for reprogramming the initial sub routines.

The control returns to the main "engine" and the "init_soil_water" module. This module assigns values to the soil water variable arrays, such as field capacity, saturation, hydraulic conductivity, wilting point, refill point and two growth limiting factor values for each soil layer (see Section 5.7.11). These values can be manipulated through the user interface before running the program.

The next module to be called from the main "engine" is the "initialize" module. This module sets up the tables that store the output from the program. These tables can then be used after the program is run to view and summarise the output. In this "initialize" module, the visual basic function "Randomize" is called to initialise the seed for the random number generator to create the values for the random variables used in the Monte Carlo simulation. As the program is run, an index number is incremented for each day and this is initialised to 1 in this module. The rain state is a variable that stores the number of days there

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has been continuous rain and this is set to zero at this point. Several modules are then called to initialise values for the graphical interface.

5.7.2 Central Module of the Program

After the "initialise" modules are completed, the main program commences. The program consists of an outer loop for the number of years and two inner loops. The first inner loop cycles twelve times, once for each month of the year. Within this loop the "set_up_months " module is called to calculate the number of days in the month, which is stored in a variable. There is also an IF statement to take account of leap years for the month of February.

The first part of this module accesses the tables in the database that contain the probability distributions for the monthly rainfall. These tables have the name "rain" and <month number>. For example, the table storing the probability distribution for January is called "rain1". The number of records in this table is stored in a variable and is used in a later module to obtain the rainfall based on a random number (see Section 5.7.6). The generation of these probability distributions comes from the actual rainfall data stored in the database and will be described in Chapter 6.

5.7.3 Fertiliser and Manure Additions

The first call in the daily loop is to the "fert_check" sub routine. This subroutine checks whether the current day, month and year matches any of the dates for manure and fertiliser additions in the table called "Manure and Fertiliser Additions". If this is true then the program determines whether the addition is manure or fertiliser.

If the addition is manure, a variable is assigned the value "True"; and "False" if the addition is a fertiliser. The first layer of soil is then incremented by the amount of nutrient added in the fertiliser, which is calculated from the "fertiliser query". This query multiplies the application rate by the ratio of each nutrient that is contained in the fertiliser addition.

The control then returns to the main module and if the manure addition variable is true, then the "manure" subroutine is called. In the manure subroutine, the stochastic nature of the manure's physical and chemical characteristics are captured by randomly sampling some of these values. Empirical relationships from monitoring data are used for the rest of the variables. These relationships are detailed in Chapter 6.

The dry matter percentage of the manure is determined by sampling from the probability distribution of this variable. The distribution of the manures' dry matter percentage is assumed to be normal and the algorithm used to generate the value of the random variate is the polar method outlined by Law and Kelton (1991).

5.7.4 Generating a Normally Distributed Random Variable

The polar method of Law and Kelton (1991) was found to be from 9% to 31% faster then other methods of generating normally distributed random variates, and is used in the EMU model to obtain the dry matter percentage, and other random values. The method requires the generation of two uniformly distributed random variates, U_1 and U_2. These uniformly distributed random variates are used to produce two independent identically distributed normal random variates, X_1 and X_2. Only one of these random variates is used each time. The algorithm is outlined in steps 1 to 4 below.

1. Let $V_i = 2U_i - 1$ for $i = 1, 2$ and

2. Let $W = V_1^2 + V_2^2$

Repeat step 1 and 2 until $W > 1$

3. Let $Y = \sqrt{(-2\ln(W)/W}$

4. $X_1 = V_1 Y; \quad X_2 = V_2 Y$

The random number generator in Access is used to generate the required uniformly generated random numbers, and a statistical test of the output of this random number generator is included in Chapter 6. Another random number is generated to determine whether X_1 or X_2 will be used to transform the standard normal variable to a random variable from the distribution of interest. If the random number generated is less than 0.5, then X_1 is used and if greater than or equal to 0.5, than X_2 is used. The mean and standard deviation of this distribution is used to return the required value by setting:

$X' = \mu + \sigma X_{1 \text{ or } 2}$

where

X' is the random variable of interest.

The characteristics of the stockpiled manure are described in Chapter 6. Aluminium concentrations in the stockpiled manure were found to be normally distributed and most of the other elements were shown to have a reasonable to strong correlation with it (see Chapter 6). Therefore, to determine the concentrations of each nutrient in each addition of manure, a concentration for aluminium is found by sampling its normal distribution and the values for the other nutrients are then determined from the empirical relationships found in the dataset.

Total nutrients (kgs) is found by multiplying the percentage of nutrient in the manure by the amount of manure added and the dry matter percentage. The addition of manure increases the depth of the first horizon and this depth is incremented with the depth of manure added, by dividing by the manure density. Any compaction of manure is not considered in the calculation of the new depth. The new CEC for the top horizon is also calculated, based on the exchangeable cations in the added manure and the original CEC for that horizon.

New cation exchange constants are calculated by calling the subroutine "cation_exchange_constants". The cation solutions that are present in the soil at this point in time are used to calculate these constants. A

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preferable value to use would be the amount in solution in the soil at equilibrium. However, these data are not available at this time.

5.7.5 Planting and Harvest Dates

The control returns to the main program and the "plant_harvest_days" subroutine is called. This subroutine determines where in the crop cycle the program is and reassigns values to the following variables where necessary; number of days after planting, the crop weight and crop nutrient uptake, which are reset to zero if it is a harvest day.

5.7.6 Rainfall and Evaporation

The control again returns to the main program, which calls the "rain_module" subroutine to generate the rainfall. In this module another random number is generated and the "find_rain_prob" subroutine is called to determine if rain occurs on a particular day. This is determined by looking up the first column of a rainfall transition matrix that has been obtained from rainfall data stored in the database.

The rainfall transition matrix stores the probabilities of rain occurring on any day, given there was rain on each of the preceding x number of days. If the random number that has been generated is less then the probability of rain occurring for the particular state (number of continuous rain days) then the number of continuous rain days is set to zero and no rain is generated for that day. If the random number is greater than this probability, then the number of continuous rain days is incremented by 1. Chapter 6.1 outlines the development of the transition matrix.

If rain occurs on any given day, another random number is generated, which is used to find the amount of rainfall for that day. The subroutine to return the amount of rain for the day is called "find_prob" and is also used to generate the amount of evaporation for the day. The arguments passed to this subroutine are:

- the month number and table name - used to determine which table of probability distributions to access;
- number of records in this table - found previously in the "set_up_months" subroutine;
- the random number;
- cumulative probability;
- corresponding rainfall (or evaporation) value; and
- the probability for the interval.

The random number is used to determine the value of the random variate (in this case rainfall) by sampling the piecewise distribution and was described in Rubinstein (1981). This method, rather than the polar method, is used, as the probability distributions of monthly rainfall data are available. The piece-wise constant probability distribution and the algorithms used to sample the distribution are given below (Rubinstein 1981).

$$f_x(x) = \begin{cases} C_i, & x_{i-1} \leq x \leq x_i; \quad i = 1,2,....,n \text{ where } C_i \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

Denote $P_i = \int_{x_{i-1}}^{x_i} f_x(x)dx, i = 1,....,n$

$$F_i = \sum_{j=1}^{i} P_j$$

$$F_0 = 0$$

$$F_x(x) = \sum_{j=1}^{i} P_j + \int_{x_{i-1}}^{x_i} C_i dx = F_{i-1} + C_i(x - x_{i-1})$$

where

$i = \max_{j}\{j : x_{j-1} \leq x\}$

Solving $F_X(X) = U$ with respect to X :

$$X = x_{i-1} + \frac{U - F_{i-1}}{C_i}, \text{ where } F_{i-1} \leq U < F_i$$

The steps used to return the random variate (X) are:

1. Generate U from a uniform distribution between 0 and 1.

2. Find i from : $\sum_{j=1}^{i-1} P_j < U \leq \sum_{j=1}^{i} P_j \quad i = 1,....,n$

3. $X = x_{i-1} + \dfrac{U - \sum_{j=1}^{i-1} P_j}{C_i}$

The probability distributions are stored in tables for each month. Table 5.1 presents the probability of rainfall for the month of January. The probability distributions of rainfall and evaporation for each month are included in Appendix C and D respectively.

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Table 5.1. Piece-wise Probability Distribution for January Rainfall

i	x	Probability Density
0	0	0.088
1	5	0.038
2	10	0.032
3	15	0.011
4	20	0.007
5	25	0.007
6	30	0.001
7	35	0.001
8	40	0.003
9	45	0.001
10	50	0.001
11	55	0
12	60	0
13	65	0.001
14	70	0
15	75	0.001

The program loops through the appropriate table and calculates the cumulative probabilities for each rainfall increment (5 mm). When the cumulative density is greater than the random number, the lower rainfall bound (x column in Table 5.1) is stored. Control then returns to the rain module and the rainfall for the day is found from the algorithm given in step 3 above. The rainfall value is stored in the simulation data table, which updates various graphics for the user interface.

The evaporation subroutine is called next by the program. This subroutine uses the probability distributions to select the evaporation from the data stored in the database in a similar way to the rainfall. The major difference is that a value for evaporation is required daily. The same subroutine as used in generating the rainfall ("find_prob") is used to generate evaporation.

The next part of the program sums the rainfall for the previous 5 days. The sum of the rainfall on the 5 previous days is used to determine which distribution to sample from for the various effluent nutrient concentrations (see Chapter 6.3). The summation is done within the main module and uses an Access aggregate function (Dsum). The criteria of this function is the index number less than or equal to the current index number and greater than the current index number – 5. There is an "IF" statement to sum the first rainfall values when the index number is less than 5.

5.7.7 Irrigation Module

The "irrig_module" module is the next subroutine called. The first part of the irrigation module tests if the program is using real data or is in Monte Carlo simulation mode. If it is using real data then the amount to irrigate is read from the appropriate table. For the Monte Carlo simulation mode, another "IF" statement is entered. If the number of days since planting is greater than 20, then the program determines if all the layers are below the refill point. The refill point for each layer is determined at the beginning of the program and is the point halfway between wilting point and field capacity for each layer. A loop is then

entered for each layer of soil to determine if the soil moisture is above the field capacity for that layer. If this is the case in any layer, then the amount to irrigate is set to zero and the subroutine is exited. If the number of days since planting is less than 20 then the program determines whether the soil moisture in the first layer only is above wilting point. If this is the case then the amount irrigated is set to zero and the subroutine is exited. If the code progresses through to the next execution of code then irrigation is required.

The amount to irrigate is found by summing the difference between field capacity and the soil moisture for each layer. The irrigation sub routine is only called when there is a crop in the ground and when irrigation does occur the soil profile is filled regardless of the rooting depth at that time. The "irrig_nutrients" subroutine is then called to determine the concentration of each nutrient in the effluent used as the irrigation source. The first line of code in the "irrig_nutrients" subroutine assigns a uniformly distributed random number between 0 and 1 to the "rand_num" variable. The next part of the code uses this random number to determine the EC of the effluent, which is then used to calculate the concentration of various nutrients in the effluent.

5.7.8 Determining the Characteristics of Effluent

There are two distributions that are sampled to obtain the EC of the effluent, depending on the amount of rain in the previous 5 days. These distributions are detailed in the Chapter 6.3 and are assumed to be lognormal. Because the distribution is lognormal, the exponential of the random variate returned from sampling a normal distribution is taken to obtain the EC of the effluent.

Linear relationships obtained from effluent data are used to find the concentrations of Na and Mg as a function of EC. Ca and K are then found from the concentration of Mg. (see Chapter 6.3 for the statistical analyses of these relationships).

There was no relationship found between the inorganic N concentration and any other element in the effluent. Therefore, the inorganic N concentration is determined statistically by sampling from two lognormal distributions. The first distribution is used when the rainfall for the previous 5 days is less than 20mm and the second when this value is greater than 20mm. The same subroutine is used to sample from a normal distribution with the mean and standard deviation of the lognormal distribution sent as arguments. The concentration of inorganic N in the effluent is found from the exponential of the random variate returned from the "normal_dist" subroutine. The concentration of organic N is a function of inorganic N, as found from data stored in the database (see Chapter 6.3).

The organic P is found in the same manner as the inorganic N using two distributions. The first for when the rainfall for the previous 5 days is less than 10mm and the second for when the previous 5 days rainfall is greater than 10mm. The ortho-P is found from its relationship with organic P (see Chapter 6.3). The

rationale for using the different cumulative rainfall totals over the previous 5 days for N and P is detailed in Chapter 6.3.

The control then returns to the main program. If the amount to irrigate is greater then zero, all the irrigation is added to the soil moisture in the first soil layer and a module ("add_irrig") is called to distribute the soil water and added nutrients.

5.7.9 Distribution of Moisture and Nutrients through the Soil Profile

The development of the EMU model assumed that runon banks divert "clean water" from the irrigation area. Therefore, the only moisture input into the soil layer comes from direct rainfall and/or irrigation. There is also no consideration given to overland or lateral flow originating up gradient.

Local variations in infiltration rate occur because of differences in soil structure, compaction, initial moisture content and profile down the soil and in vegetation density (Morgan 1995). When soil profiles have two or more layers with different hydraulic conductivities, the infiltration behaviour becomes complex (Wild 1988). These variations are quite difficult to model.

The first line of code in the "add_irrig" subroutine declares several one and two dimensional arrays. The one-dimensional arrays store the runoff and excess from each layer. The two-dimensional arrays are used to store nutrient concentrations and the gross amount of nutrient in the soil solution for each nutrient in each soil layer. The first loop of this subroutine initialises the runoff and excess moisture for each layer to zero.

The next line of code calls the "total_eff_nut_added" subroutine to calculate the total amount of each nutrient added, by multiplying the concentration of the nutrient by the amount of irrigation applied. The cumulative amount of each nutrient added is also stored in its respective array. The variable recording the cumulative number of effluent applications is also incremented. This is used to re-dimension two dynamic arrays, the first of which stores the day the application was made and the second stores the amount of organic N that was applied. This information is used in a subroutine called later from the main program that mineralises the organic N remaining from each application of manure and effluent. The control then returns to the "add_irrig" module.

Temporary arrays that store the amount of each nutrient in the soil solution for the first soil layer, are assigned the value present in the soil solution before the irrigation application and are incremented by the amount added by the irrigation. These amounts are total kilograms per hectare per depth of soil layer. For the remaining layers, the temporary soil solution arrays are assigned the amount present in the particular soil layer before the irrigation application. In the case of both the organic forms of P and N, these arrays are assigned zero. The program assumes that these forms stay in solution for only one day and are therefore only able to be leached or lost in runoff on the day of application. The organic N can again be

lost through these pathways once it has been mineralised to an inorganic form. The program then enters a loop for each soil layer and calculates the amount of excess moisture and runoff from each layer.

The first "IF" statement in the loop determines if the soil moisture is above the saturated moisture of the profile. When this is the case then the amount assigned to the excess array is the difference between the current soil moisture and the saturated value. If this daily excess is greater than the saturated hydraulic conductivity (mm/day), then the difference between the daily excess and the saturated hydraulic conductivity is assigned to the runoff and the amount infiltrating to the next layer is the saturated hydraulic conductivity. If the daily excess is less than the saturated hydraulic conductivity, then the runoff is zero for that layer. If the soil moisture is less than the saturated moisture content then both runoff and excess are assigned zero.

Excess soil moisture and soil nutrients are redistributed from the top layer through the profile, and the soil moisture in each layer is incremented by the excess moisture from the previous layer. Excess and runoff for the current layer is then subtracted from the corresponding soil moisture. The nutrient concentration for each layer is then the total amount of nutrient in the layer divided by the soil moisture. The amount of nutrient to be transferred is calculated from several "IF...THEN" statements that divide the nutrients up into the runoff and excess components. Nutrient concentrations for each layer are then recalculated to account for the amount lost to drainage and runoff. The soil solution arrays are then updated with the values stored in the temporary arrays.

If there is a rainfall event, a similar module "add_rainfall" is called and the soil moisture and nutrients are redistributed. The final part of the "add_irrig" module assigns the organic form of P added in the irrigation and remaining in the soil (i.e. not lost to drainage or runoff) to the adsorbed store. Similarly any organic N that was added in the effluent and still remaining in the soil solution is assigned to the organic store and is therefore no longer available for leaching.

The next subroutine to be called from this module is the "drain_and_redist_cats" subroutine. The first loop of this subroutine updates the array that stores the cumulative amount lost to drainage for each nutrient. Two loops are then entered; the outer loop steps through each layer and the inner loop calculates the amount of each cation in the soil and in solution, which is converted to mequiv/cm^3. Two-dimensional arrays storing these values are then sent to the subroutine "cation".

5.7.10 Cation Exchange

The "cation" subroutine is used to calculate the amount of each cation exchanged from adsorbed to the soil solution, or visa versa. Exchange of cations from the soil solution to the soil matrix occurs with varying degrees of difficulty. Rate of exchange is a function of the exchange complex characteristics and the effective size and charge of the competing ions. For the most part, however, exchangeable cations are

freely replaceable (Iskander 1981). The "cation" subroutine attempts to represent the important cation exchange processes by using the Gapon exchange equations provided by Frissel & (Reiniger 1974).

The first calculation in this subroutine is the ratio of the soluble Na to the adsorbed (or exchangeable Na). This ratio (x_1) is calculated for each layer and is used as the first estimate to solve for the actual value, based on the exchange constants calculated in the "cation_exchange_constants" module in the initialisation part of the program and when manure is introduced into the system.

The sum of the four adsorbed cations (in mequiv/cm^3) is the cation exchange capacity (CEC). By using the relationships given in Equation 5.1 to Equation 5.3 and knowing the total amount of each cation, a Newton-Raphson iteration is used to solve for x_1 in Equation 5.4 in the "newton_raphson" subroutine (adapted from Frissel & Reiniger 1974). Note Equation 7.5 in Frissel & Reiniger (1974) is incorrect.

$$CEC = \frac{Na_{tot}}{1+x_1} + \frac{K_{tot}}{1+x_1 X_{Na,k}} + \frac{Ca_{tot}}{1+x_1^2 X_{Na,Ca}} + \frac{Mg_{tot}}{1+x_1^2 X_{Na,Ca} X_{Ca,Mg}} \quad ....\text{Equation 5.4}$$

where

$Na_{tot} = Na_{sol} + Na_{ads}$

$K_{tot} = K_{sol} + K_{ads}$

$Ca_{tot} = Ca_{sol} + Ca_{ads}$

$Mg_{tot} = Mg_{sol} + Mg_{ads}$

$Na_{sol}, K_{sol}, Ca_{sol}, Mg_{sol}$ = amount of each cation in the soluble form

$Na_{ads}, K_{ads}, Ca_{ads}, Mg_{ads}$ = amount of each cation in the adsorbed form

$X_{Na,k}, X_{Na,Ca}$ and $X_{Ca,Mg}$ are the exchange contstants, and

$$x_1 = \frac{Na_{sol}}{Na_{ads}}$$

The main problem with the Newton-Raphson numerical method is that the root it converges to may not be the one required (Gerald & Wheatley 1989, pp 15-17). Using a starting value close to the root should alleviate this problem, hence using the ratio of the current Na in solution to that adsorbed. Frissel & Reiniger 74) suggested that the iteration may not converge using Equation 5.4, but this problem has not become apparent in any of the runs of the EMU model to date.

5.7.11 Crop Growth

Whisler (1978) recommended the use of algebraic type equations to account for the soil water balance when modelling for the purpose of planning irrigation requirements, drainage system capacities, waste water renovation systems and some plant growth models. In these cases, it is only necessary to know how much water enters and leaves each soil profile (Whisler 1978). This is the approach used in the next subroutine, the "crop_growth_rate" module, which is called if there is a crop in the ground. The algorithms used for this module have been developed using the WaterMod help files (Johnson 1998).

The crop growth rate module used in the EMU model calculates the potential growth rate as a function of the current dry weight of the crop. The logistic equation that the EMU model uses is given in Equation 5.5 (Johnson 1998).

$$\frac{dW}{dt} = \mu \left(\frac{W + \alpha}{W_f + \alpha} \right)$$ ....**Equation 5.5**

Where

W is the crop dry weight (kg/m^2),

t is the time in days,

W_f is the potential yield (kg/m^2),

is a dimension coefficient and has the units of day^{-1}, and

α (kg/m2) is a scaling parameter and is a function of the time of maximum growth rate:

$\alpha = W_f \exp(-\mu t^*)$,

where

t* is the time of maximum growth.

The potential yield, period of maximum growth rate and water use efficiency for each crop is stored in a table in the database. For Tullimba, the potential yields are obtained by averaging crop data collected over the last 3 years for sorghum and oats. The period of maximum growth are those reported in Doorenbos (1984). The water use efficiencies used as default values are 600 mm/kg crop dry weight for C3 plants and 300 mm/kg crop dry weight for C4 plants (Johnson 1998).

The potential yield and α are adjusted daily, and the growth rate, which is a function of the soil water available for transpiration, is affected by water stress. Several other variables are also incremented on a daily basis; the number of days after planting, potential yield, daily growth rate and two growth limiting factors (Johnson 1998).

The daily growth limiting factor (glf) is the ratio of the actual transpiration rate to the potential transpiration rate. The weighted mean growth limiting factor (GLFmean) is the sum of the daily growth limiting factors divided by the number of days the plant has been growing. This is used to adjust the scaling factor, α, daily, as shown in Equation 5.6 (Johnson 1998).

$\alpha = W_f \exp(-GLF_{mean}\mu t^*)$ ....**Equation 5.6**

A table in the database stores the soil moisture content at which the growth limiting factor is 1 for each soil layer. These are read into their respective variables at the beginning of the program and can be adjusted by the user before the program is run. The first variable that is calculated is the transpiration demand, which is simply the daily crop growth rate, multiplied by the water use efficiency.

If the soil water is less than wilting point, the growth limiting factor is set to 0 and there is no crop growth. If the soil water content is between the moisture content where the growth limiting factor first becomes 1 and the field capacity for the soil, the growth limiting factor = 1. Between these two points the growth limiting factor is a linear function of the soil moisture content. The algorithms for when the soil water (sm) is between wilting point (wp) and the point where the growth limiting factor first becomes 1 (glf_upper) is shown in Equation 5.7 and the algorithm for when the soil water is above field capacity (fc) in Equation 5.8 (Johnson 1998).

$$glf = (sm - wp) / glf\_upper \quad\text{...Equation 5.7}$$

$$glf = (sat - sm) (1 - glf\_sat) / (sat - fc) + glf\_sat \quad\text{...Equation 5.8}$$

Where

sat is the saturated soil water content (mm),

sm is the soil water content (mm),

fc is the field capacity (mm),

wp is the wilting point (mm),

glf is the growth limiting factor,

glf_sat is the value for the growth limiting factor at saturation, and

glf_upper is soil water where growth limiting factor = 1.

The next line of code in the crop growth module looks up the crop's root distribution "froot" for each soil layer where the root density function uses a stepped approach similar to that employed by Fitzpatrick and Nix (1969) for their evapotranspiration functions. This information is stored in a table in the database and can be changed by the user. The root distribution is a discrete function of days after planting and the default values are from Doorenbos *et al.* (1979).

The preferential module from WaterMod (Johnson 1998) has been used to determine the actual transpiration from each soil layer. Water uptake is determined by the growth limiting factor multiplied by the root distribution, multiplied by the soil water above wilting point, with all these variable being different for each layer.

The four cations in solution are summed for each layer and converted to EC (dS/m) using Equation 5.9 (Gardner *et al.* 1993). The average of the EC for each layer is then used to calculate the percentage yield reduction (Y_r) shown in Equation 5.10 (Maas 1996).

$$EC = \frac{TDS}{640} \quad\text{...Equation 5.9}$$

Where

TDS is the Total Dissolved Salt (mg/L).

$$Y_r = 100 - b(EC - a) \quad \text{... Equation 5.10}$$

Where

Y_r = percentage yield reduction,

a = the salinity threshold expressed in (dS/m),

b = the slope expressed in (%/dS/m),

EC = the mean electrical conductivity of a saturated-soil extract taken from the root zone (dS/m),

For barley: a = 8.0 dS/m and b = 5 %/dS/m (during seeding stage 'a' should be < 5 dS/m), and

For sorghum: a = 6.8 dS/m, b = 16 %/dS/m.

Equation 5.9 is a saturation extract value and differs from the EC of the soil solution by a factor equal to the ratio of the saturated moisture content to the current moisture content. This ratio is approximately 2 for a soil that has a moisture content near to filed capacity (Smith, R. 1999, pers. comm., 6 Sep). Therefore the effect of omitting this relationship in the model is to overestimate the predicted yields.

The nutrient uptake from each layer is then calculated and deficiencies are recorded in arrays for each nutrient. Control returns to the main module from where the "soil_evap_module" subroutine is called.

5.7.12 Soil Evaporation

The soil evaporation module is adapted from the WaterMod Help Files (Johnson 1998). The potential soil evaporation is a function of ground cover and the evaporation value calculated earlier. The ground cover (g_cover) is a function of the crop dry weight (W) and the crop dry weight for 90% light interception ($W90$) (Johnson 1998). The equations used are shown in Equation 5.11 and Equation 5.12. The actual soil evaporation is limited to the top two layers (400 mm depth). If the soil moisture in the top two layers is below field capacity, then the ratio of the soil moisture to field capacity is used to limit the amount of actual evaporation from that layer (Johnson 1998).

$$\text{g\_cover} = 1 - (\text{Exp}(-k\, W)) \quad \text{... Equation 5.11}$$

where

g_cover = percentage ground cover,

W = crop dry weight (kg), and

$$k = \frac{\log(10)}{W90} \quad \text{... Equation 5.12}$$

where

$W90$ = crop dry weight for 90% light interception (kg).

Control then returns to the main module and the "redistribute_sm" subroutine is called to redistribute the soil moisture. Figure 5.3 is a schematic of the distribution of the soil moisture throughout the profile used in the program. Rainfall or irrigation is added to the first layer, and depending on the antecedent moisture conditions, the soil water is redistributed to the lower soil profiles, runoff or drainage. The nutrients are

also redistributed as a function of the amount in solution and the cations are exchanged as outlined in Section 5.7.10.
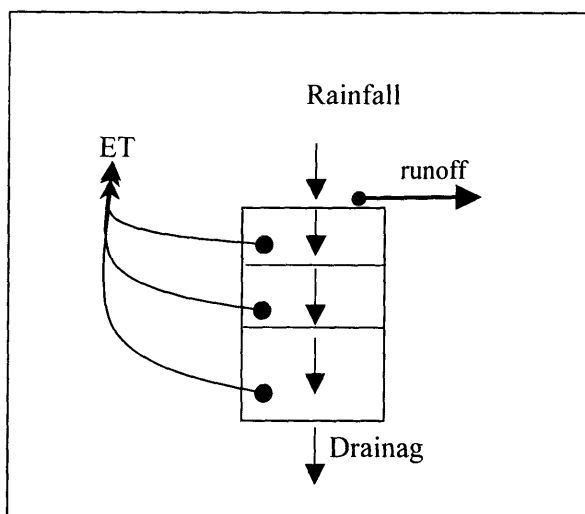

Figure 5.3. Soil Moisture Distribution

5.7.13 Mineralisation

The final module in the program calculates the amount of organic N mineralised to an inorganic form each day. An important consideration when selecting a mineralisation model is the number of parameters required as inputs to the model. A simple nitrification model provided by Chae and Tabatabai (1986) has only two inputs: time since application (t) and a first-order rate constant (k), which is shown Equation 5.13. This author is not aware of how the daily amounts were calculated.

$$N_m = N_o[1\text{-exp}(-kt)] \quad \dots\dots\dots\dots\dots\dots \textbf{Equation 5.13}$$

where

N_m is the amount mineralised,

N_o is the amount of organic N available for mineralisation,

k is a first-order rate constant, and

t is time since application.

Scott *et al.* (in press) modified this equation to include three rate constants. These rate constants decrease when 80% and 65% of the original organic N has been mineralised, corresponding to 188 and 218 days after application respectively. The Excel solver function is used in the Chapter 6 to find appropriate rate constants using these data as a guide. After the amount mineralised each day is calculated, it is transferred from the organic to the inorganic N pool and is available for leaching and plant uptake.

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Chapter 6.   Model Inputs

Assembling model inputs and investigating the relationships between input variables is the comprehensive stage of model development. The objective of this stage is to focus on the relationships that are central to the basic mechanisms within the system (Gaunt *et al.* 1997). The understanding of these relationships leads to an improved understanding of the important processes that operate within the system. This understanding can be developed through the investigation of collected datasets and using them to simulate the system (Gaunt *et al.* 1997).

Model inputs should be simple, capable of being replicated, feasible in terms of financial and physical constraints, have a broad applicability and be understandable (Park & Seaton 1996). A measure of the resource base is also required for comparison of future trends (Kruseman *et al.* 1996). Therefore, a simulation model should be intrinsically linked with the monitoring program that will provide input data.

6.1   Rainfall

Climatic variation has a large influence on any agro-ecosystem, hence it is important to capture the characteristics of climatic variables that are used as inputs to the model (Holton 1996). Historical rainfall records are not directly used as inputs, but provide the characteristics of seasonal rainfall patterns. These patterns, such as several consecutive days of rainfall associated with the passing of a front, and summer storms, which are short and intense, were obtained by using monthly rainfall distributions and probabilities of consecutive rain days.

There were three options for obtaining data to provide the characteristics of the rainfall patterns. The first was to use data from a continuously recording weather station, which was installed at the Tullimba feedlot in June 1995. However, several lightning strikes disrupted data recording and the measurements are incomplete. The second option was to use manual rainfall records, which have been recorded at Tullimba since February 1994. Although this dataset is accurate and complete, it is of limited length in terms of extracting the characteristics of the rainfall pattern. The final option was to use the rainfall records from the Kingstown weather station, which span 15 years from 1981 to 1996.

The Kingstown weather station is located approximately seven kilometres to the south west of the feedlot. Given the close proximity of the Kingstown weather station to Tullimba, the longer Kingstown dataset should provide the essential characteristics of the rainfall. A longer dataset is preferential for use as input to a stochastic model as it will include more extreme events and therefore increase the likelihood of these occurring in the simulation. Figure 6.1 is a scatter graph of the relationship between the Tullimba manual rainfall records and the Kingstown weather station records, which indicates the record sets differ most for small rainfall events. This is likely to be a result of isolated summer storms and the relationship is considered strong enough to indicate the preference for using the much longer Kingstown rainfall records.
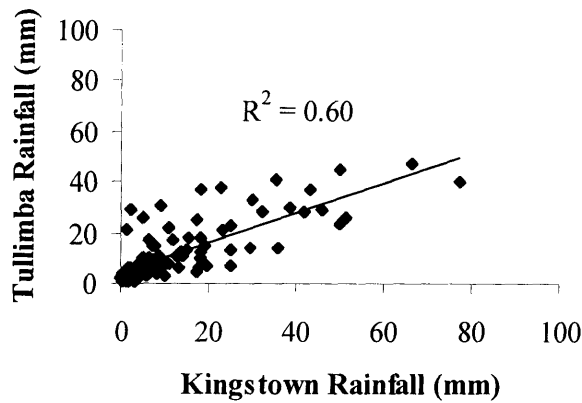
Figure 6.1. Comparison of Kingstown and Tullimba Manual Rainfall Records (mm)

A first-order two-state Markov chain model (see Shaik & Bate 1996) was investigated as a means of characterising the rainfall pattern. The Markov chain model calculates probabilities for a wet day followed by a wet, or dry day and a dry day followed by a wet, or dry day. The transition probability matrix of this type of model has only four probabilities and traditionally is used for short-range weather forecasting (Shaik & Bate 1996). However, the first-order two-state Markov chain model is not able to satisfy the criterion of characterising the seasonal rainfall pattern and a transition matrix was developed to characterise these rainfall patterns.

The quantities transition matrix method presented by Clarke (1984) was the first attempt at capturing characteristics of rainfall sequences, using a 10 mm rainfall interval. Each interval defines a state variable, which is used to determine the probability of "y" rainfall depth following "x" rainfall depth on two consecutive days. Seven state variables are used and their ranges are shown in Table 6.1, with n_{ij} being the number of times that state i is followed by state j. For example, n_{01} is the number of times in the observed rainfall sequence that 'no rain' is followed by daily rainfall ≤ 10 mm.

Table 6.1. Rainfall States and Corresponding Rainfall Intervals (r = Daily Rainfall Total (mm))

State	Rainfall Range
0	$r = 0$
1	$0 < r \leq 10$
2	$10 < r \leq 20$
3	$20 < r \leq 30$
4	$30 < r \leq 40$
5	$40 < r \leq 50$
6	$50 < r$

	0	1	2	3	4	5	6
0	n_{00}	n_{01}	n_{02}	n_{03}	n_{04}	n_{05}	n_{06}
1	n_{10}	n_{11}	n_{12}	n_{13}	n_{14}	n_{15}	n_{16}
2	n_{20}	n_{21}	n_{22}	n_{23}	n_{24}	n_{25}	n_{26}
3	n_{30}	n_{31}	n_{32}	n_{33}	n_{34}	n_{35}	n_{36}
4	n_{40}	n_{41}	n_{42}	n_{43}	n_{44}	n_{45}	n_{46}
5	n_{50}	n_{51}	n_{52}	n_{53}	n_{54}	n_{55}	n_{56}
6	n_{60}	n_{61}	n_{62}	n_{63}	n_{64}	n_{65}	n_{66}

The average rainfall event for each month from the simulated data using the transition matrix method was compared with the average rainfall event for each month from Kingstown. The average rainfall event from the simulation was approximately twice the actual (see Figure 6.2). To obtain a better representation of the average rainfall event for each month, this transition matrix was modified to calculate the probability of rain occurring on "x" consecutive days.

The rainfall data were analysed to calculate probabilities that 0, 1 , 2 .... 9 or more days of rainfall are followed by a fine day, which are shown in Table 6.2. The method requires the generation of a random number, which is compared with the transition matrix probabilities to determine if rain occurs. If rain does occur, than the piecewise rainfall probability distribution for the particular month is sampled and compared to the random number, which returns the amount of rainfall (see Chapter 5.5.1).

Table 6.2. Probability of No Rain Following "x" Number of Continuous Rain Days

Number of Days of continuous Rain	Probability
0	0.83
1	0.50
2	0.55
3	0.46
4	0.61
5	0.65
6	0.5
7	0.5
8	0.33
9	0.4

Figure 6.2 compares the averages of three, ten year simulations using the method of sampling the monthly piecewise rainfall probability distribution and the probability of rain occurring on any given day, the Kingstown averages and the average rainfall event of the Clarke's (1984) quantities transition matrix outlined above. This graph indicates that the method using the quantities transition matrix for the probability of "x" mm following "y" mm is far less successful than the method of using the probabilities of a rain day following "x" rain days.

Given the better performance of the method using probabilities of a rain day following "x" rain days, this method was incorporated into the Effluent and Manure Utilisation (EMU) model and the monthly distributions of the simulated and Kingstown rainfall were compared. Figure 6.3 provides the histograms of the monthly data for the simulated and Kingstown rainfall and also the histogram for all rainfall data (top histogram in Figure 6.3). Table 6.3 presents the p-values for the Wilcoxon rank-sum test (Millard 1998), which tests significant differences between the means of the samples. This test does not rely on data being normally distributed. All p-values are greater than 0.05 and therefore at the 5 % significance level, the distributions are similar.
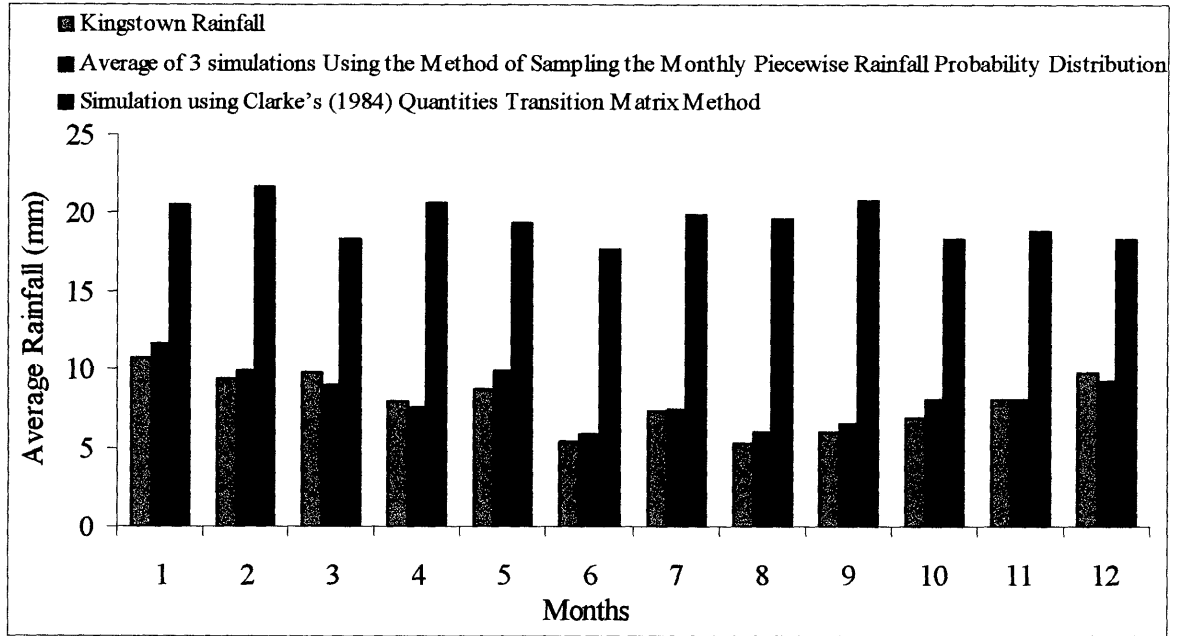
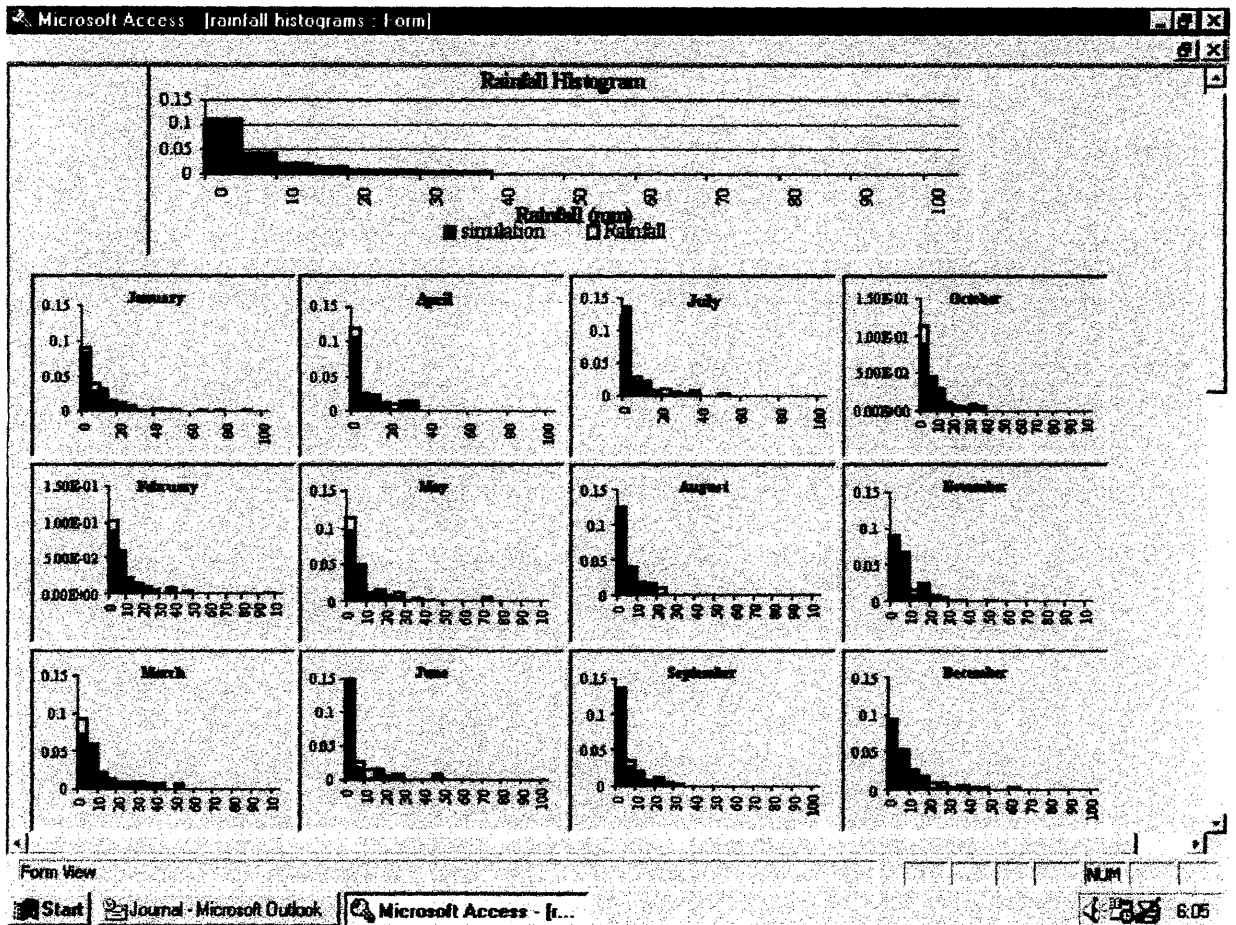**Figure 6.2. Average Rainfall Event For each Month of Historical and Simulated Rainfall Data**

Figure 6.3. Comparison of Histograms of Simulated and Actual Rainfall Data

Table 6.3. p-values for Comparison of Simulated and Acutal Rainfall Distributions

	p-value Wilcoxon rank-sum test
All Data	0.34
January	0.15
February	0.81
March	0.17
April	0.39
May	0.90
June	0.90
July	0.31
August	0.68
September	0.08
October	0.44
November	0.96
December	0.15

6.2   Evaporation

The only evaporation records available are those collected from the Tullimba weather station from 10th June 1995 to the 24th May 1998, totalling 769 records, with 310 missing. Evaporation was simulated using piecewise monthly distributions of evaporation data and as indicated in Figure 6.4, the time series of the simulated data compares closely to the data collected from the weather station. The seasonal trend, as characterised by a wandering mean and a non-stationary variance is evident for both the simulated and measured data, with the variance being higher for the higher evaporation values. Figure 6.5, a comparison of the averages and standard deviations of the simulated and measured data, demonstrates that the simulation has replicated the seasonal characteristics of the evaporation.
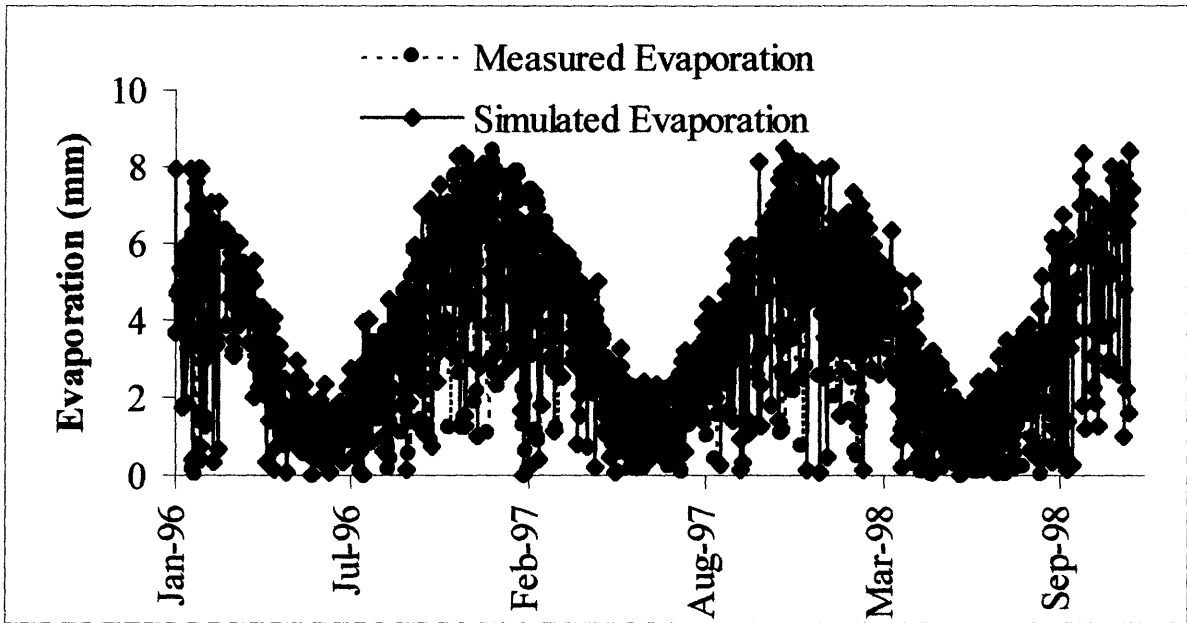
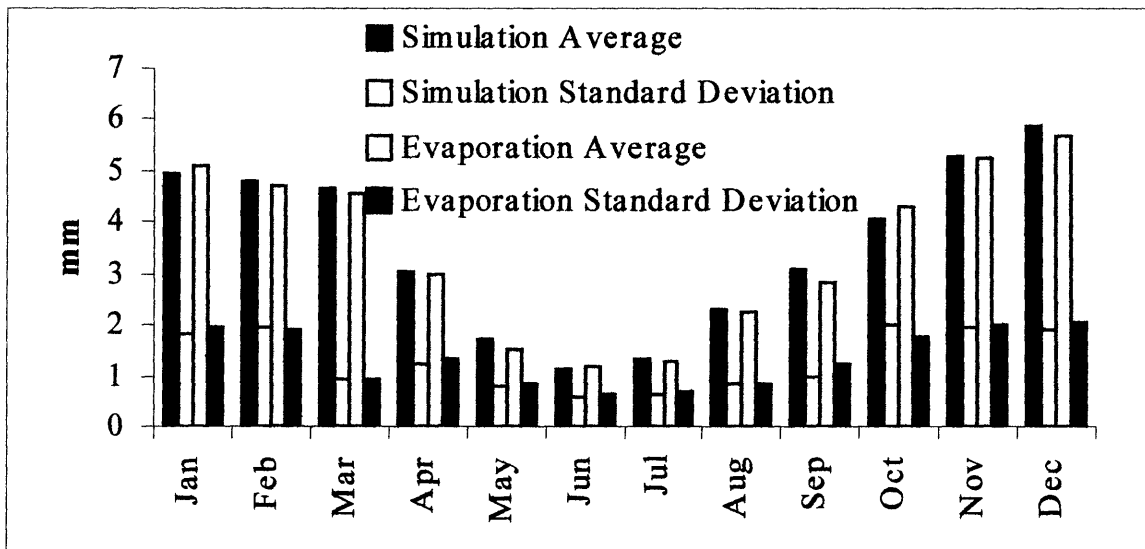**Figure 6.4. Simulation and Actual Time Series of Evaporation Data**

Figure 6.5. Simulation and Evaporation Data Averages and Standard Deviations

6.3　Effluent Characteristics

To prevent soil salinity problems through the improper application of effluent and to predict chemical and biological transformations and transport of nutrients within the soil profile, a thorough understanding of the changes that take place in stored effluent is required (Iskander 1981; Linderman & Ellis 1978). The main characteristic of stored effluent is the variation in the nutrient concentrations over time, which is a result of many factors.

6.3.1　Sampling the Effluent

Feedlot runoff quality is a function of stocking density, ration, rainfall intensity and duration and efficiency of the settling ponds (Eigenberg *et al.* 1995; Linderman & Ellis 1978). This runoff is collected and stored in holding ponds where further biological and chemical changes take place due to the settling of solids, microbial activity, evaporation, and dilution by direct rainfall (Linderman & Ellis 1978). During the course of this study, samples were taken from the holding ponds on a monthly basis over several years. The EC and pH of these effluent samples were measured and further analyses measured the concentrations of the cations, N and P, along with other elements.

Due to the large variability of effluent quality, the EC and soluble salt concentration should be checked regularly when the effluent is used as an irrigation source (Linderman & Ellis 1978). Without this sampling it would not be possible to accurately account for the amount of each nutrient being added to the soil. Hence, environmental degradation could occur through the application of excess nutrients that could escape to the wider environment.

Another important reason for sampling is to understand the composition of the effluent compared to that of the soil solution to which it is being applied. Stored effluent from a beef cattle feedlot in the Unites States has been reported to contain between 240 to 1850 *ug/g* of K compared with the 5 to 20 *ug/g* K concentration of most soil solutions (Olsen & Barber 1977). This has implications for the cation exchange complex in the soil and can cause soil stability problems. The amount of K adsorbed in an exchangeable form is a function of the proportion of Na to Ca and Mg, (i.e. SAR) in the applied water (Stewart & Meek 1977). The higher the SAR, the higher the soil exchangeable Na will become (Stewart & Meek 1977) and excess Na in the effluent can cause soil dispersion (Linderman & Ellis 1978).

Table 6.4 is the effluent quality data from the two holding ponds at the "Tullimba" feedlot and also provided are the values from various sites in the Unites States. Included in the table are surface runoff data from feedlot pens reported by Stewart and Meek (1997).

Table 6.4. Comparison of Effluent from Tullimba Feedlot Holding Ponds and Various Sites in the United States (Linderman & Ellis 1978; Stewart & Meek 1997)

Chemical Analyses		Tullimba Feedlot		Linderman & Ellis (1978)		Stewart & Meek (1997)		
		Holding Pond 1	Holding Pond 2	Site 1	Site 2	Texas	Nebraska	Kansas
Total solids	mg/L	967	690	2420	4587			
Volatile solids		227	307	1149	2107			
Total N		9.4	5.7	73	113			
NH4-N		2.2	1.4	32	38			
Total P		3.2	6.0	28	56			
K		45	61		825	1329	2542	704
Ca		18	21		31	441	802	261
Mg		16	19		55	207	498	97
Na		51	51		212	598	851	299
SAR		2.3	2.1		5.3			
EC	dS/m	0.48	0.53	1.38	3.05			
pH		8.8	8.7	8.5	7.8			

In Table 6.4, the differences in the Tullimba effluent data to the values reported from sites in the United States, are likely to be a result of the feedlot rations and climatic influences. While the average data shown in Table 6.4 varies significantly between geographical locations, Linderman and Ellis (1978) found that EC varied greatly and erratically within a dataset. The averages reported by Linderman and Ellis (1978) in Table 6.4 were from a dataset that ranged from 0.29 to 2.75 dS/m. Stored effluent EC from Tullimba ranged from 0.18 to 1.42 dS/m for the measurement period. Some of the variability in the measurements can be attributed to evaporation, which tends to concentrate the soluble salts in the pond and on the feedlot surface, from where they are transported via runoff to the pond. EC levels in the pond will vary according to evaporation, but can also be associated with the solids content of the runoff (Linderman & Ellis 1978).

Effluent pH averages reported in Table 6.4 do not show great variation between the locations, however there is large variation within the included datasets. The pH in the "Tullimba" dataset ranges from 7.12 to 9.77 and in the Linderman and Ellis (1978) dataset, from 7 to 9.5. These changes in pH are a function of the concentrations of other elements in the effluent. For example, increasing pH decreases microbial activity and P solubility and increases NH_4-N loss (Linderman & Ellis 1978).

6.3.2 Electrical Conductivity (EC) of Effluent

The EC of the effluent is related to the concentration of ions in solution and is an easily measured parameter. Therefore, data form the Tullimba dataset were investigated in an attempt to extract simple relationships between the EC and the other parameters, such as concentrations of Na, K, Ca, Mg, N and P that could be used as inputs to the EMU model. Before undertaking the investigation between EC and the concentration of various ions in solution, EC data were graphed to obtain an understanding of their distribution. At the Tullimba feedlot facility, the effluent is stored in two holding ponds and differences in the distributions of the EC of the effluent from the two holding ponds were investigated. Figure 6.6 shows

the density histograms of the EC from the two holding ponds, and indicates a greater variation in Holding Pond 1 with a few extreme outliers and a lower average than Holding Pond 2.
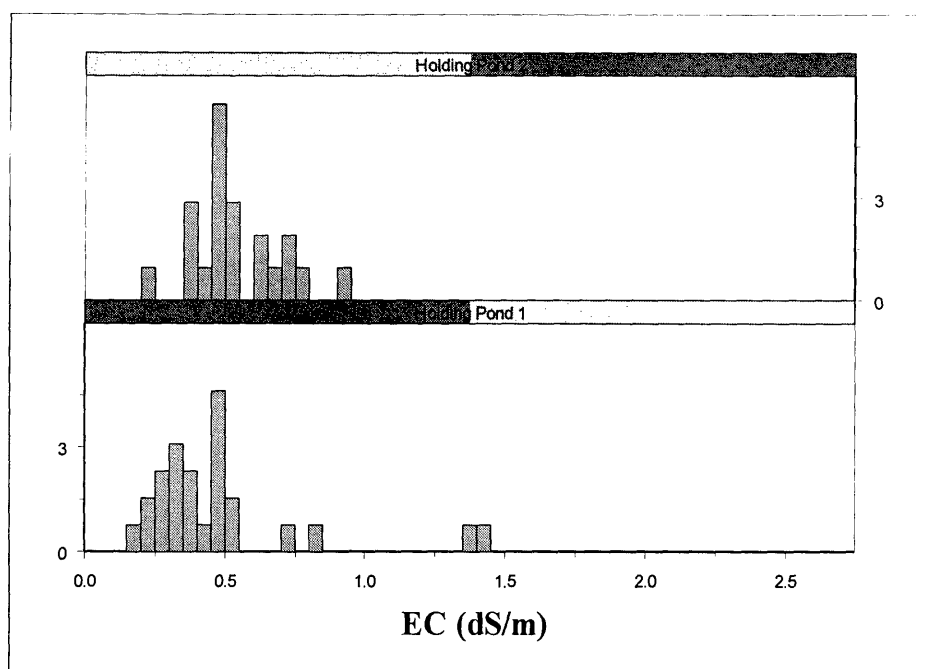

Figure 6.6. Density Histograms of EC of Effluent from the two Tullimba Holding Ponds

These differences in the distribution of the effluent EC from the two holding ponds may be a result of the occasional transfer of effluent from holding pond 2 to holding pond 1 and recycling of effluent from the terminal pond to holding pond 1. To increase the size of the dataset and capture the greatest variation, data from both holding ponds were combined and used in the statistical analyses of the relationships between EC and the parameters of interest.

When there are several days of no rainfall and high evaporation, the stable ions in solution will become more concentrated, while the volatile ions such as ammonia, will be lost from the system. In contrast, rainfall producing runoff will introduce a flush of ions into the holding ponds. The quantity of rainfall producing runoff is dependent on the antecedent conditions of the catchment. Therefore, the EC of the effluent should be a function of the amount of rainfall in some previous time period. Investigations of the data did not reveal any significant relationship between EC and rainfall and/or evaporation.

Even though there is no significant relationship evident between EC and rainfall or evaporation, it was important to incorporate the effects of the rainfall on the EC of the stored effluent into the EMU model. To achieve this, data were investigated to observe the effects of rainfall and evaporation on the distribution of the EC. Two distinct distributions of the effluent EC were observed as a function of the amount of rainfall in the previous 5 days. This being when the total rainfall was less than or greater than 15 mm. The results of the goodness-of-fit tests for these distributions are shown in Figure 6.7 and Figure 6.8. These results show that the lognormal distribution is an adequate fit for these data, given the limited data set of 30 EC values for total rainfall in the previous 5 days < 15 mm and 17 EC values for total rainfall in the previous 5 days > 15 mm.
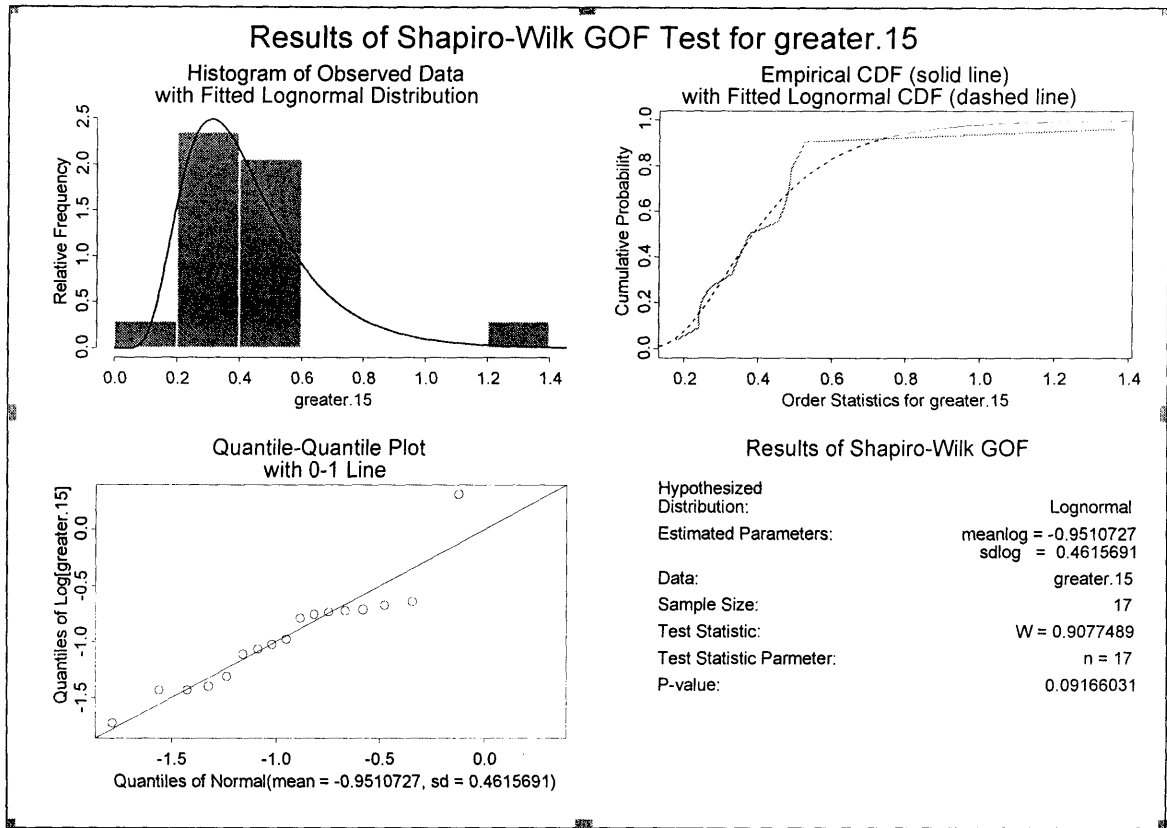
115

Results of Shapiro-Wilk GOF Test for greater.15

Histogram of Observed Data with Fitted Lognormal Distribution

Empirical CDF (solid line) with Fitted Lognormal CDF (dashed line)

Quantile-Quantile Plot with 0-1 Line

Results of Shapiro-Wilk GOF

Hypothesized Distribution:	Lognormal
Estimated Parameters:	meanlog = -0.9510727
	sdlog = 0.4615691
Data:	greater.15
Sample Size:	17
Test Statistic:	W = 0.9077489
Test Statistic Parmeter:	n = 17
P-value:	0.09166031

Figure 6.7. Goodness-of-fit tests for Effluent EC when Total Rainfall for the Previous 5 days > 15mm (greater.15)

Results of Shapiro-Wilk GOF Test for less.15

Histogram of Observed Data with Fitted Lognormal Distribution

Empirical CDF (solid line) with Fitted Lognormal CDF (dashed line)

Quantile-Quantile Plot with 0-1 Line

Results of Shapiro-Wilk GOF

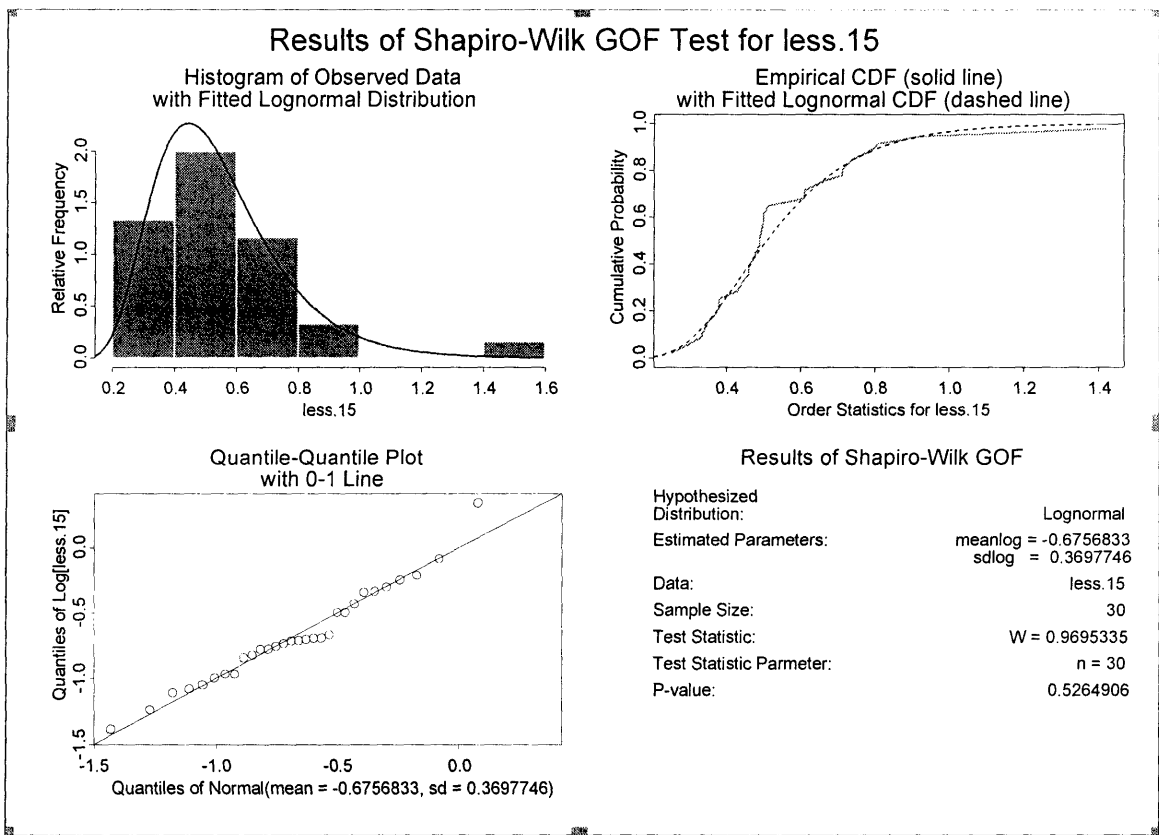|	
Hypothesized Distribution:	Lognormal
Estimated Parameters:	meanlog = -0.6756833
	sdlog = 0.3697746
Data:	less.15
Sample Size:	30
Test Statistic:	W = 0.9695335
Test Statistic Parmeter:	n = 30
P-value:	0.5264906

Figure 6.8. Goodness-of-fit tests for Effluent EC when Total Rainfall for the Previous 5 days < 15mm (less.15)

As outlined in the model development section (Section 5.7.4), a module is included in the EMU model to randomly sample from the normal distribution. This module requires only the mean and standard deviation of the distribution as input to return the value of the random variate required. Even though the module is designed to sample from a normal distribution, a lognormal distribution can also be sampled by transforming the returned normal variate using the exponential function.

To randomly sample the effluent EC distributions, a random number is generated and sent to the sub routine to sample from a normal distribution. The value returned from sampling the normal distribution is transformed to a lognormal variate. In this way the EC of the effluent used for irrigation on any given day is stochastic in that the value is randomly selected, but also incorporates some effects of rainfall by the use of the two distributions.

6.3.3   Concentrations of Cations in Effluent

If significant relationships exist between the EC of the effluent and the concentrations of the parameters of interest then this should be used in the model. In this way the EC can be used as the stochastic "seed" for the characteristics of the effluent. It was in this context that data were investigated for simple linear relationships between EC and the nutrients of interest and relationships between the nutrients themselves.

The EMD was used to investigate relationships of the various nutrients with the EC of the effluent using the 47 samples from both holding ponds. The relationships found are shown in Figure 6.9 and show that Mg and Na have reasonably linear relationships with the EC of the effluent and Ca and K with Mg.
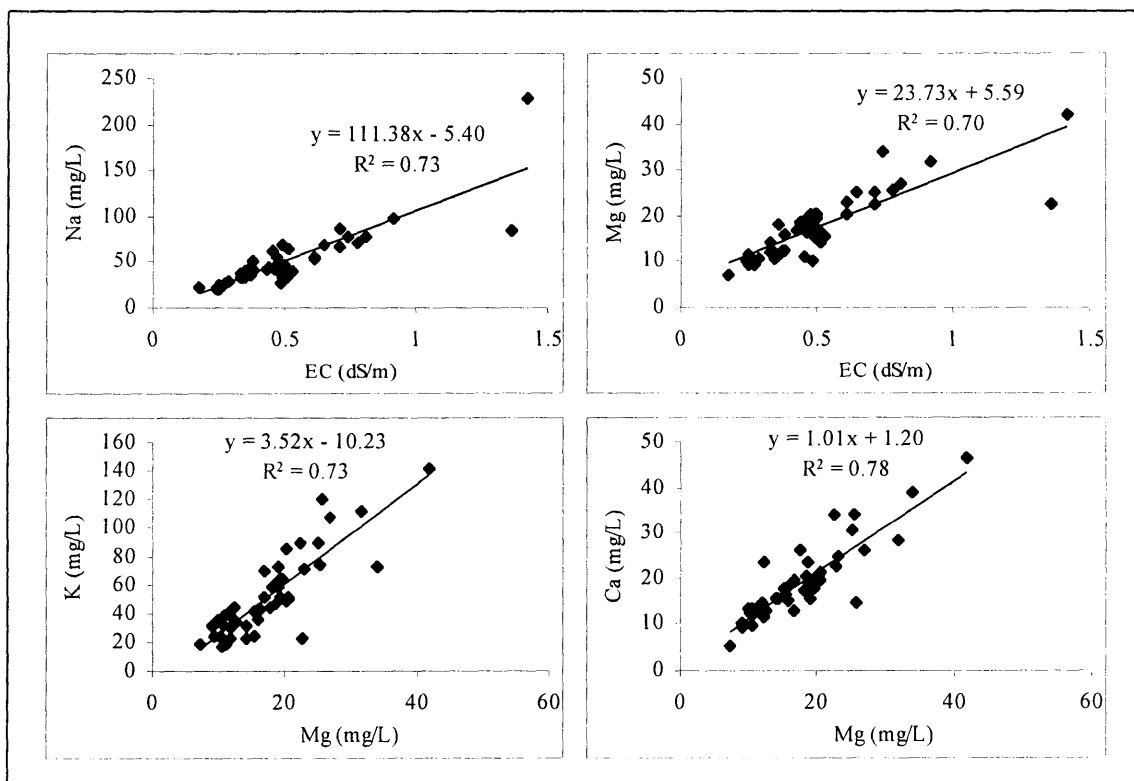

Figure 6.9. Relationships Between Effluent EC and Na, Mg, Ca and K

6.3.4 Nitrogen and Phosphorus Concentrations in Effluent

Several forms of N in the effluent are quite volatile and therefore it is difficult to extract any relationships with the other variables in the dataset. Linderman and Ellis (1978) found that the proportion of N as NH_4 varied with time, which is important in the context of using effluent as an irrigation source, as NH_4 constitutes most of the N readily available to plants. A factor which adds to the difficulty involved in predicting the concentration of NH_4-N in effluent, is its increased volatility when it is aerated, as is the case when applied through a travelling irrigator, particularly if the effluent is alkaline.

Given the unpredictable nature of inorganic N concentrations in effluent, and assuming that rainfall producing runoff will produce a flush of N into the holding ponds, an investigation of the distributions of inorganic N as a function of total rainfall in the preceding days was carried out in a similar manner as for EC. Distributions of N as a function of rainfall totals for the previous 5 days were investigated, as the rainfall total for this period is already calculated in the EMU model. This investigation revealed two distinct distributions of inorganic N ($NO_3 + NH_4$) as a function of the total rainfall in the previous 5 days, being greater or less than 20 mm.

The movement of P from the feedlot pad to the storage facility occurs primarily in proportion to the solids transported (Eigenberg *et al.* 1995). Therefore P should be positively correlated with the total solids in effluent. This was confirmed by some data presented by Linderman and Ellis (1978) who found that concentrations of P in the effluent ranged from 12 mg/L to 90 mg/L. However, this relationship was not found in data collected from Tullimba, and even though most of the P produced in faeces ends up in the manure stockpile, there is a proportion in solution, which is found in the effluent. The same approach used for the generating a value of EC and inorganic N in effluent is used for P.

Total P was used and two distributions as a function of rainfall in the preceding two days were extracted from the dataset. The total rainfall greater than, and total rainfall less than 10 mm for the preceding 5 days was found to produce two distinct lognormal distributions. Goodness-of-fit tests for these variables were performed, indicating that at the 5% significant level, a lognormal distribution does not fit these data very well, particularly for rainfall in the previous 5 days less than 10 mm. However, given the limited number of data points, the difficulties in sampling another distribution and in an attempt to decrease the complexity of the model, the lognormal distribution was used. This will require further verification as more data is collected as part of the monitoring program. The averages and standard deviations used to sample the distributions to return the random values for N and P concentrations in the effluent are shown in Table 6.5.

Table 6.5. Averages and Standard Deviations for Nitrogen and Phosphorus as a Function of Total Rainfall in the Preceeding 5 Days

	Lognormal Parameters			
	Mean	Standard Deviation	Mean	Standard Deviation
	Total Rainfall Previous 5 days			
	< 20 mm		>20 mm	
Inorganic nitrogen	-0.027	0.893	0.113	1.43
	< 10 mm		>10 mm	
Total phosphorus	1.80	1.00	2.05	0.621

Only four effluent samples have had both inorganic and total N analyses performed. These four data points are used to obtain a linear relationship between total N and inorganic N, which is used in the EMU model to return the amount added to the organic N pool. Similarly for total P and ortho-P, a linear relationship is used to divide the P between the organic and inorganic pools. The relationships used for N and P are shown in Figure 6.10.
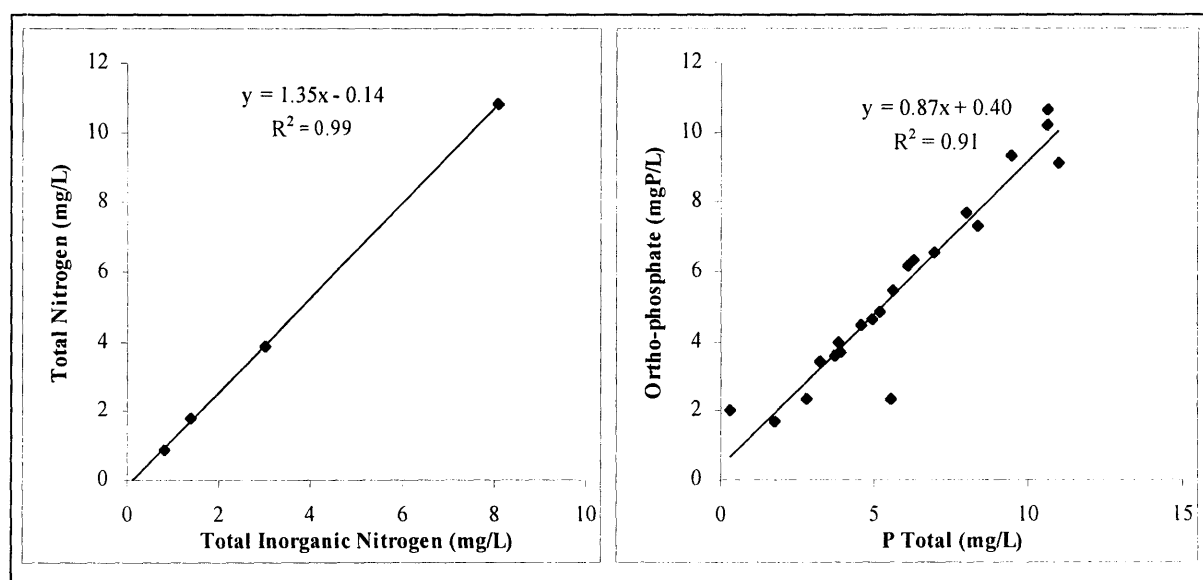

Figure 6.10. Relatioships Between the Inorganic Forms of Nitrogen and Phosphorus and the Totals for Each of the Nutrients in Effluent

6.4 Manure Characteristics

Nutrient concentrations in manure are a function of animal species, ration type, method of manure collection and time in storage (Eigenberg *et al.* 1995; Gilmour *et al.* 1977; Kardos *et al.* 1977; Sri Ranjan *et al.* 1995; Sweeten 1991). There is also a wide variation in manure analyses from similar livestock operations (Schmitt *et al.* 1997).

Table 6.6 gives the averages and standard deviations from 10 manure samples collected in November 1996 during a manure spreading operation at the Tullimba irrigation area. In Table 6.6, these manure data are compared with various averages and standard deviations gleaned from the US literature (Shapiro 1996;

Stewart & Meek 1977). The average from the Tullimba data is generally less than the US values, however the standard deviations are much greater. This could be an indication that the uniformity of the Tullimba manure is far less than the US manure.

Table 6.6. Manure Characteristics from Tullimba and the Literature

Nutrient		Tullimba 10 Spread manure samples Nov 96		Shapiro (1996) Nebraska 12 feedlot stockpile samples		Nebraska Book Values	Stewart & Meek (1977) Nebraska	Kansas	Texas	Arid South West
		Ave	Std Dev	Ave	Std Dev	Ave	Ave	Ave	Ave	Ave
Total nitrogen	% Dry Weight	0.84	0.57	3.14	0.35	4.5				
Ammonium nitrogen				0.93	0.14	1.5				
Total Phosphorus		0.48	0.21	3.74	0.34	3.0				
Potassium		0.60	0.30	2.75	0.31	5.0	0.46	1.09	2.29	2.3
Sulphur		0.23	0.11	1.23	0.26					
Sodium		0.14	0.06	0.28	0.03		0.1	0.23	1.13	1.12
Aluminium		0.08	0.03							
Calcium		1.2	0.5				0.26	0.78	1.98	2.8
Magnesium		0.60	0.06				0.17	0.39	0.76	1.53
pH				7.1	0.37					

Manure characteristics vary as manure moves from the animal system though the storage system to the soil system. There is also a large variation in the characteristics of the manure within each of these systems. This variation is shown in Figure 6.11, which is based on 26 pen manure, 25 fresh faeces, 10 spread manure and 9 harvest manure samples. The fresh faeces referred to in the box and whisker plots shown in Figure 6.11, are analyses of samples obtained from fresh deposits on the pen surface. The pen manure is analyses of samples from older manure. In Figure 6.11, harvested manure refers to analyses of samples taken when the pen is cleaned out and spread manure is analyses of samples taken when the manure is applied to the irrigation area.

The volatile nature of some elements and stable nature of others is shown in Figure 6.11. The volatile nature of N is evident, with up to half being lost from the fresh faeces to the pen or harvested manure. By the time the manure is spread after stockpiling, there have been further losses. Ca and P exhibit similar characteristics to N, possibly due to losses in the soluble form. The lower concentration of K, Al and Mg in the fresh faeces compared to pen or harvested manure types suggests that these elements are in an absorbed form and as moisture is lost from the manure they become more concentrated.
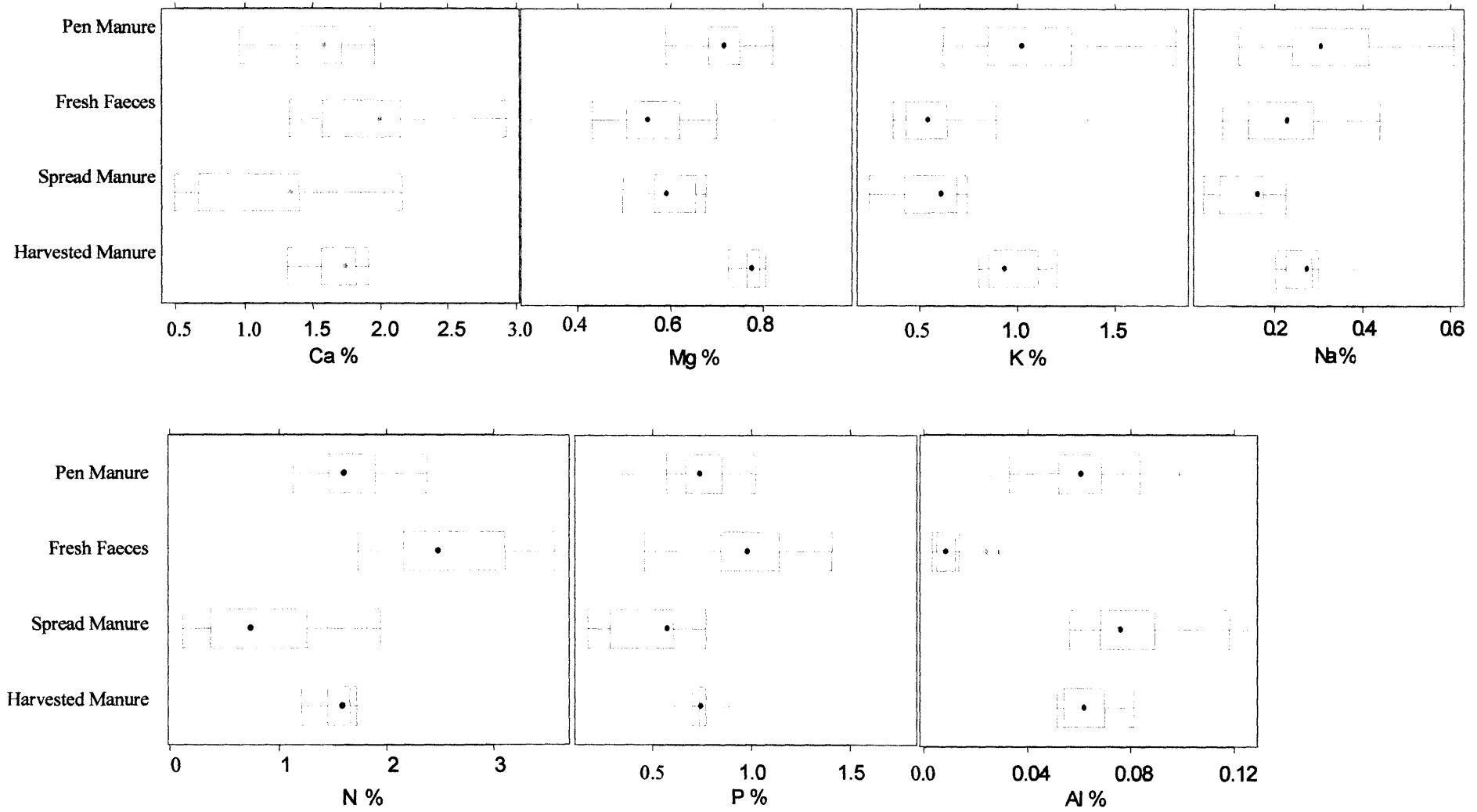
Figure 6.11. Variation in Manure Characteristics

The characteristics of the stockpiled manure should not be a function of rainfall, as a properly constructed stockpile should shed water with minimal infiltration of moisture into the stockpile. The elements in an absorbed form should have a relationship with the ration characteristics, however given the limited dataset available at the present time and the volatile nature of some of the elements, the 10 spread manure data are used to extract relationship in a similar way to the liquid effluent.

The statistical package, "S-plus" was used to investigate relationships between nutrients in the manure. Given the limited dataset, it was important to base the relationships on a variable that had a statistically significant normal or lognormal distribution. Aluminium data displayed the most normal distribution characteristics, as indicated by the diagnostics of a Shapiro-Wilk goodness-of-fit test for the 10 Al data, shown in Figure 6.12.

Aluminium is a relatively stable element in the manure, and therefore, a reasonable relationship with other stable elements should be evident in the dataset. The trellis function in "S-plus" was used to investigate the relationship of Al with the other nutrients in the manure required as input to the EMU model. Figure 6.13 is the scatter matrix that is the graphical output of the trellis function and indicates the strength of linear relationships by fitting a local regression model. The variables in Figure 6.13 are indicated in the white boxes down the diagonal of the figure. Each graph in the same row and column as a variable indicate the relationships that variable has with the other variables included in the analyses. Therefore, each graph has a mirror image rotated 90 degrees, with one above and one below the diagonal. The straighter the line of the local regression model, the stronger the linear relationship, for example, the first graph on the second row indicates a reasonably linear relationship between the concentration of total P and Al in manure.

"S-plus" was then used to test the significance of the strongest linear relationships. The graphs of the relationships with the linear regression and r^2 values are shown in Figure 6.14. These relationships are used in the EMU model to determine the characteristics of the manure each time it is added to the soil system.

The density of the manure and its dry matter percentage are also required as an input to the EMU model. These variables are functions of the position of the manure in the stockpile and the length of time the manure has been stockpiled. An average of 70 % dry matter and a standard deviation of 20 % is used to sample the assumed normal distribution (Powell 1997; Watts *et al.* 1994).
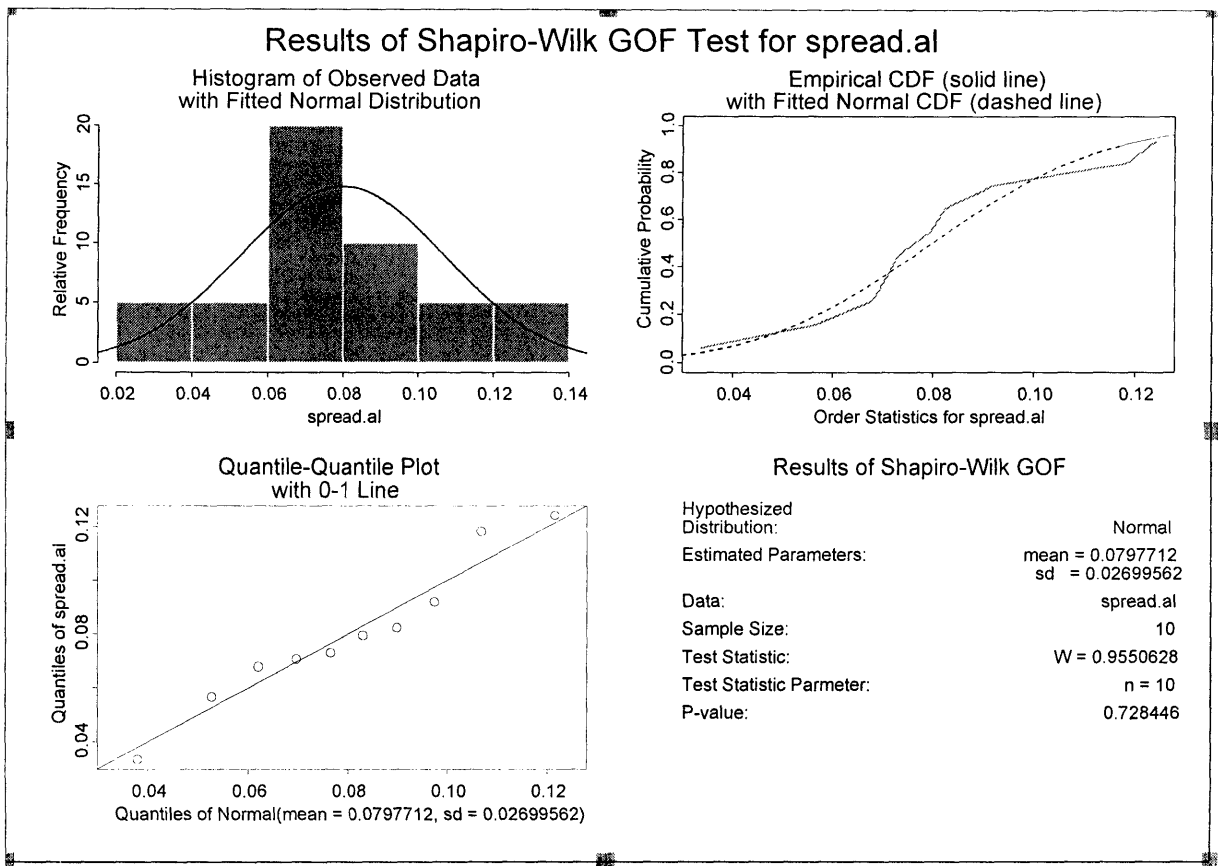
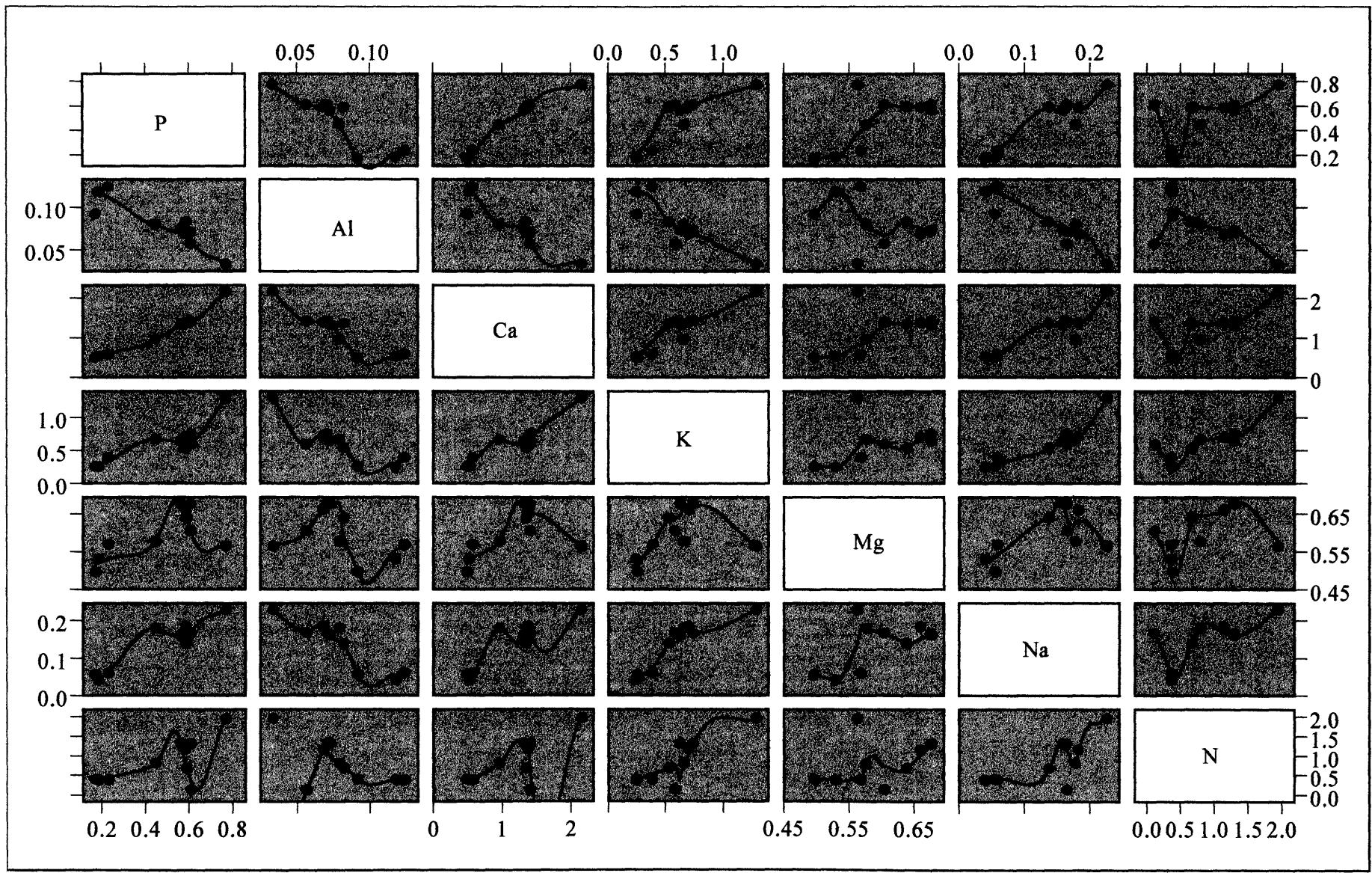Figure 6.12. Goodness-of-fit Test for Al % in Spread Manure

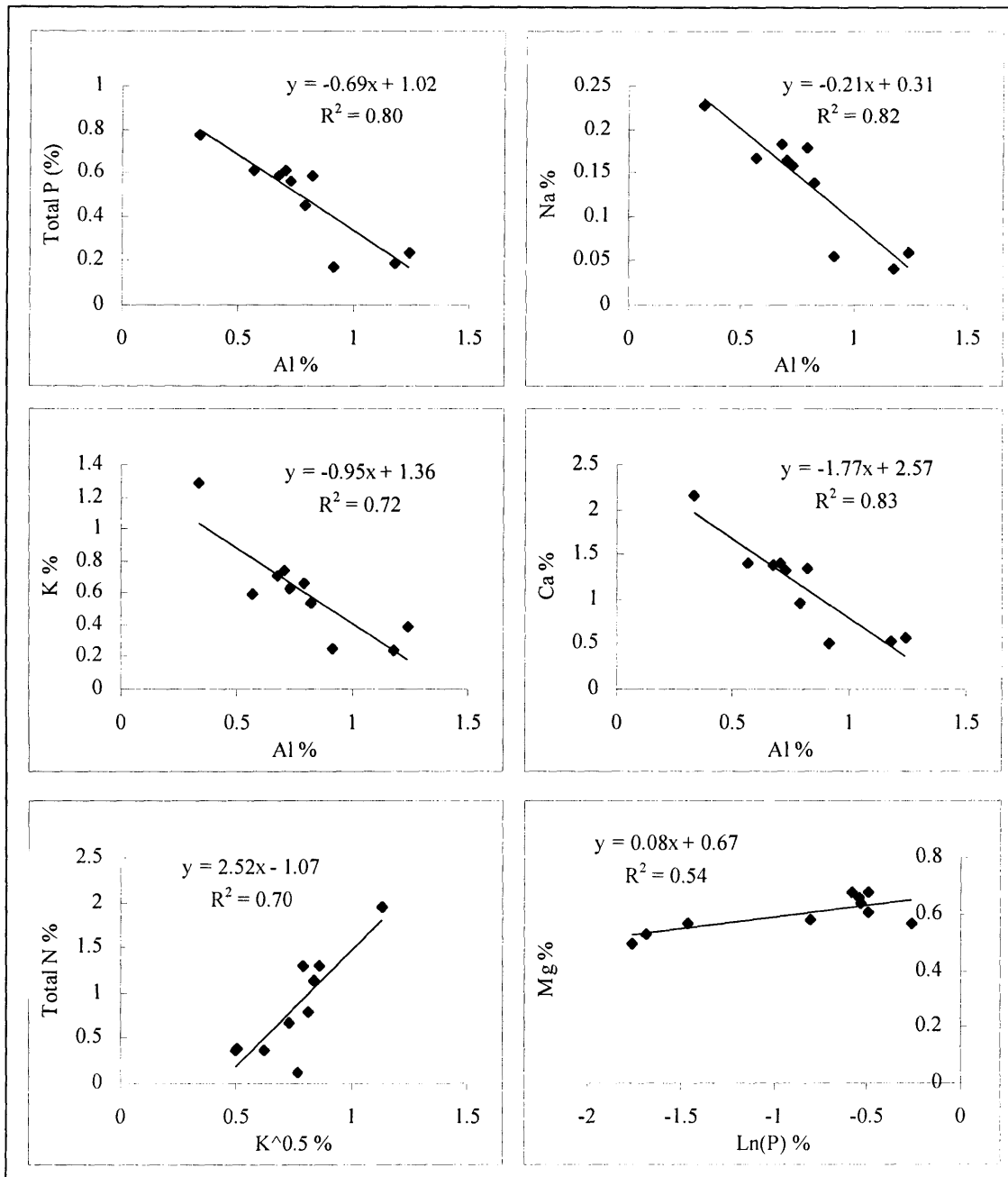**Figure 6.13. Scatter Matrix of Manure Characteristics (%)**

Figure 6.14. Linear Relationships of Manure Characteristics Used in EMU Model

6.5 Crop Data

The potential yields used in the crop growth module of the EMU model are obtained from the average yields for each crop grown over the three previous years at the Tullimba feedlot facility. Forage sorghum and oaten silage are the two crop types that have been grown and included in the model at this point. The yield averages, used as potential yields in the model, for forage sorghum and oaten silage are shown in Table 6.7. Also included in Table 6.7 are the period of maximum growth for each crop (Doorenbos 1984) and the water use efficiency values (Johnson 1998) used in the EMU model.

Table 6.7. Potential Yield for Sorghum and Oats

Crop	Potential Yield (kg/m^2)	Period of max growth (days)	Water Use (mm)
Oats	0.81	40	600
Forage Sorghum	0.53	45	300

Table 6.8 presents the average percentage of selected nutrients removed in the oats and sorghum crops grown at Tullimba over the last three years. The sorghum samples are from two crops, with four samples taken from the first crop 14 days prior to harvest in March 1997. Seven samples were taken four days prior to the first harvest of the second crop in January 1998 and five samples were taken 7 days prior to the second harvest of the same crop in March 1998. There were only three samples from which to take the average of the uptake from the oats crop just prior to harvest. All other samples were from the crop at varying times through the growing season and were not used to obtain the average crop uptake.

Data presented in Table 6.8 are compatible with those reported in the literature for crops fertilised with manure and effluent. Kardos *et al.* (1977) reported N contents ranging from 1.2% to 2.3%, and P ranging from 0.3% to 0.5% for most crops. However, the K contents measured in the Tullimba crop are at the top end of the 0.2% to 2.4% range reported by Kardos *et al.* (1977).

Table 6.8. Average of Selected Nutrient Removed in Oats and Sorghum over Three Year Period at Tullimba (% of crop weight)

Nutrient		Oats		Forage Sorghum	
		Average	Standard Deviation	Average	Standard Deviation
P	% of crop weight	0.274	0.004	0.252	0.081
K		2.446	0.178	2.470	0.577
Ca		0.247	0.095	0.405	0.097
Mg		0.160	0.030	0.362	0.123
Na		0.180	0.074	0.056	0.109
N		1.142	0.206	1.690	0.370

6.6   Initial Values

The variables that require an initial value or some form of input data are shown in Table 6.9. The units for the input variables and the units used internally within the model are included, as is the name of the table storing the information in the database. Some of these variables have a sensitivity analysis performed on them in Chapter 7.4.

Table 6.9. Variables Requiring Initialisation

Initial Value Required	Data Source	Database Table Name	Input Units	Units Converted to in Model
Mineralisation coefficients for manure and effluent	Literature and calibrated using Excel Solver	Input N mineralisation coefficients	1/day	
Crop uptake of each of the nutrients	Average of "Tullimba" plant analyses for each crop	Crop uptake	%	kg/ha
Yield Reduction slope and intercept (function of EC)	Literature	Crop uptake		
Potential Yield	Average of "Tullimba" plant analyses for each crop	Potential Yields	kg/m^2	kg/ha
Period of maximum growth	Literature	Potential Yields	days	
Water use efficiency	WaterMod help files	Potential Yields	mm	
Soil Depth	Average of collected data	Initial soil nutrients	m	
Cations in solution	Collected data – Jan93/Sep95	Initial soil nutrients	mequiv/100gm	kg/ha/soil layer
Adsorbed cations		Initial soil nutrients	mequiv/100gm	kg/ha/soil layer
P & N in solution and adsorbed	Average "Tullimba" Data – Sep95	Initial soil nutrients	mg/kg	kg/ha/soil layer
Initial Soil Moisture	Estimated	Soil moisture	mm/layer	
Field Capacity	SOILPAR/ Hydraulic Properties Calculator	Soil moisture	mm/layer	
Saturated Hydraulic Conductivity	SOILPAR/ Hydraulic Properties Calculator	Soil moisture	mm/layer	
Saturated Soil Moisture	SOILPAR/ Hydraulic Properties Calculator	Soil moisture	mm/layer	
Wilting Point	SOILPAR/ Hydraulic Properties Calculator	Soil moisture	mm/layer	
Irrigation Refill Point	Midway between wilting point and field capacity	Soil moisture	mm	
Soil Moisture where the growth limiting function = 1	Estimated	Soil moisture	mm/layer	
Value of Growth limiting function at saturated moisture content	Estimated	Soil moisture	%	
Nutrient concentrations of various commercial fertiliser	Manufacturers	Fertiliser Compositions	Ratios	kg/ha/top layer
Manure density	Literature	User input		
Crop growth rate (mu)	WaterMod help files – Sensitivity Analyses	User input		
Root distribution	Function of days after planting – literature	Root distribution	Ratios	
Soil evaporation ground cover function (w90)	WaterMod help files – Sensitivity Analyses	User input		

6.6.1 Initial Soil Moisture Characteristics

Recent research suggests that modellers in the United States are moving away from soil testing and towards the use of soil morphology to assess the hydraulic capacity of a soil that is being irrigated with effluent (Geary & Gardner 1996). Given the heterogeneous nature of the soil and the limited data collected for some parameters compared with a lot of data collected for other parameters, this approach seems attractive.

The programs SOILPAR (Donatelli *et al.* 1996) and the Soil Texture Triangle Hydraulic Properties Calculator (Saxton 1997) were used to estimate the saturated hydraulic, field capacity and wilting point of each layer of the soil within the utilisation area at Tullimba. The inputs into the SOILPAR model varies depending on the method used and include texture, organic carbon, pH and CEC.

For the purpose of this exercise, the Baumer method was used to determine the soil water properties as it requires only the percentage of sand, silt and clay as input, as does the Hydraulic Properties Calculator. These texture data were obtained from the Environmental Impact Statement (EIS) prepared for the development of the Tullimba Feedlot (Aquila Agribusiness Pty Limited 1993). The results from the two programs are given in Table 6.10 and the average of these values is used as input to the model.

Table 6.10. Estimating the Soil Moisture Characteristics (SOILPAR – is the Soils Parameter Estimate Program and Web Site is the Hydraulic Properties Calculator (URL: http://www.bsyse.wsu.edu/~saxton/soilwatr/); Sa- Sand; Si-Silt; C-Clay)

Soil Layer →	A1			A2			B		
	Sa	Si	C	Sa	Si	C	Sa	Si	C
%>	40	40	10	40	30	30	20	20	60
Parameter	SOIL PAR		Web Site	SOIL PAR		Web Site	SOIL PAR		Web Site
Wilting point (m/m)	0.15		0.09	0.21		0.17	0.36		0.35
Field Capacity (m/m)	0.3		0.25	0.34		0.30	0.45		0.48
Sat Hydraulic Conductivity (cm/hr)			2.71			0.34			0.19

The depth of each horizon is required to determine the wilting point and field capacity in units of mm/layer and the saturated hydraulic conductivity in mm/layer/day. Again, the heterogenous nature of the soil makes this determination difficult. Figure 6.15 highlights this heterogeneity by superimposing the measured depths on a schematic view of the irrigation area and shows the average depth measurements taken over a period of time for each horizon in each irrigation bay. This figure indicates the considerable gaps in the data. Bay 5 is at the top of the slope and Bay 1 is at the toe of the slope for both the South (S) and North (N) blocks.
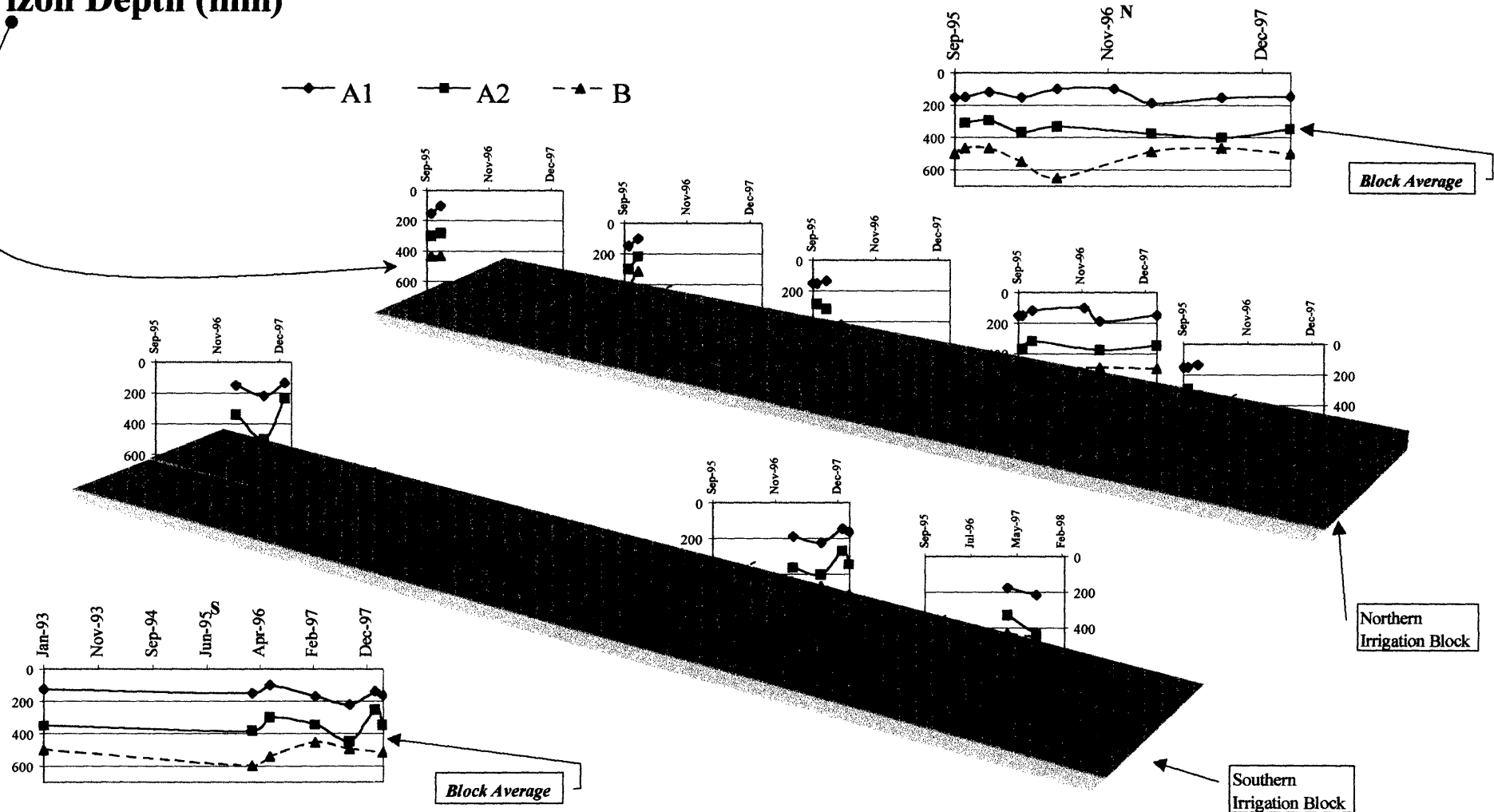
Horizon Depth (mm)

Figure 6.15. Soil Depth Measurements in the Tullimba Irrigation Area

Figure 6.16 averages the depth data shown in Figure 6.15. The depths were recorded when the soil was sampled from each horizon. The slope of the irrigation area is approximately 3% and Figure 6.16 shows that generally the depth of each horizon increases going down the slope. There were 18 samples taken on the 11th March 1996 and 27 samples taken on the 18th June 1996. The depths were recorded as averages only and are shown as S and N block averages in Figure 6.16. The S block average data also includes depths that were recorded in the 1993 EIS (Aquila Agribusiness Pty Limited 1993). The average for S1 is calculated from 3 replicates for each horizon on two dates – 4th March 97 and 11th September 97. S5 averages are taken from three sampling dates and S2 from 4 sampling dates.

Soil depth data used in the model for the A1 horizon is interpolated between the average of the finish depth of A1 and the average of the start depth of A2, similarly for the finish depth of A2. The depth to the bottom of the B horizon is obtained from EIS data and the average of 700mm (Aquila Agribusiness Pty Limited 1993) is used for the entire block. This is assumed to be the maximum depth from where the plants will be extracting nutrients.

The important characteristic required in the EMU model is the relative concentrations of each nutrient within each horizon. Some nutrients increase in concentration with increasing soil depth and other nutrient concentrations decrease down the profile. The nutrients that decrease in concentration down the profile are C, P, Mn, K and N and are shown in Figure 6.17. Even though, on average, the inorganic forms of N (nitrate and ammonium) decrease in concentration with increasing soil depth, Figure 6.18 shows when N data is viewed as a time series, this nutrient is quite mobile and the lower profiles increase in concentration as N moves through the profile.

Figure 6.19 shows that Na, Cl, Mg and Ca all increase in concentration with increasing depth of soil. As the soil is a duplex soil with a sodic B horizon this pattern is expected, particularly the increase in Na. The model is likely to be sensitive to the depth of each soil horizon that is used in the model as, for a daily mass balance, a 1% concentration over a depth of 100mm is equivalent to 17,700 kg of that particular nutrient per hectare. S1 and N1, S2 and N2 etc are on the same contour and for this reason data is pooled to obtain an average for the depth of each horizon. This is shown in Figure 6.20.
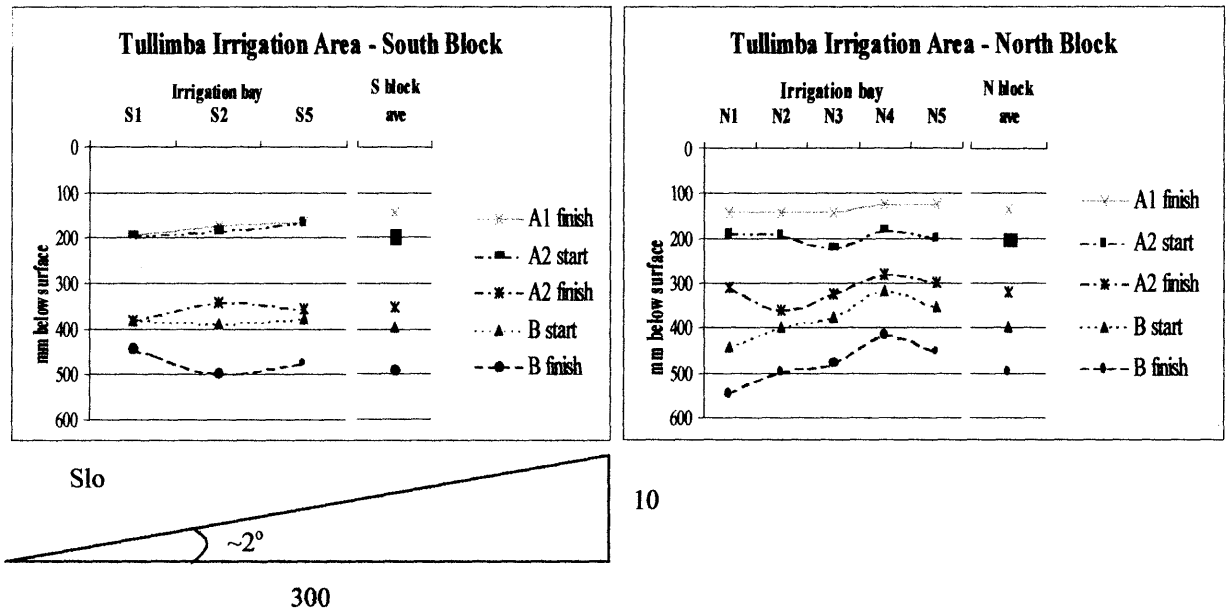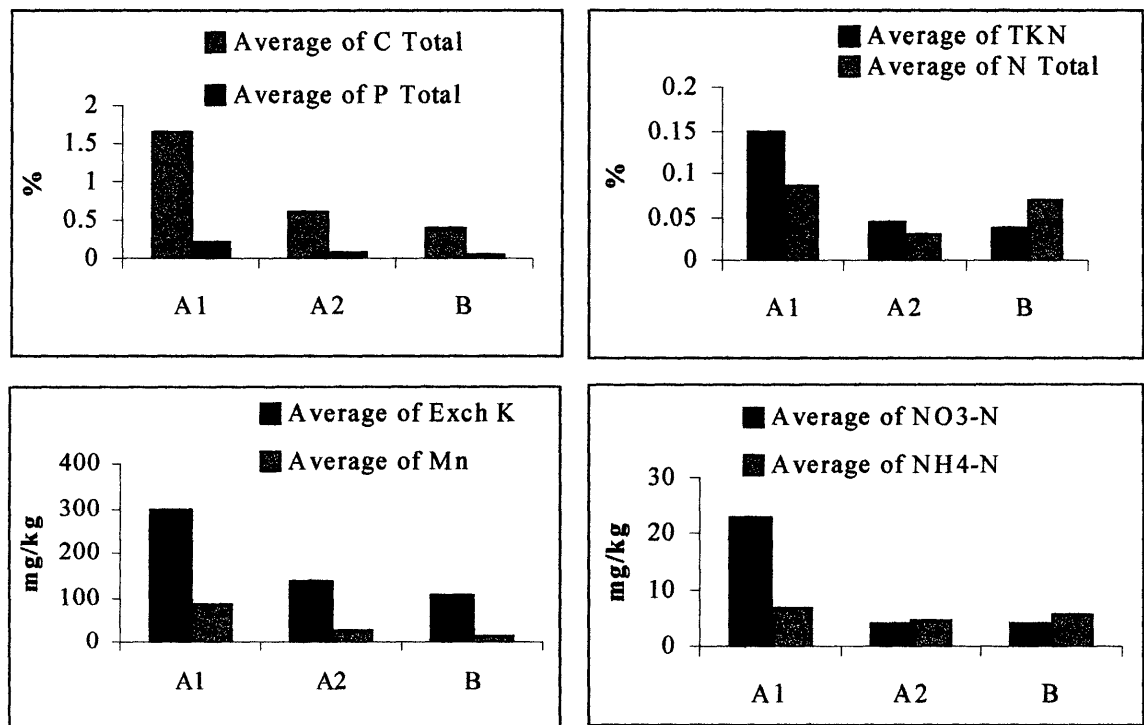
130

Figure 6.16. Average Soil Depths

Figure 6.17. Nutrient Concentrations that Decrease with Increasing Soil Depth
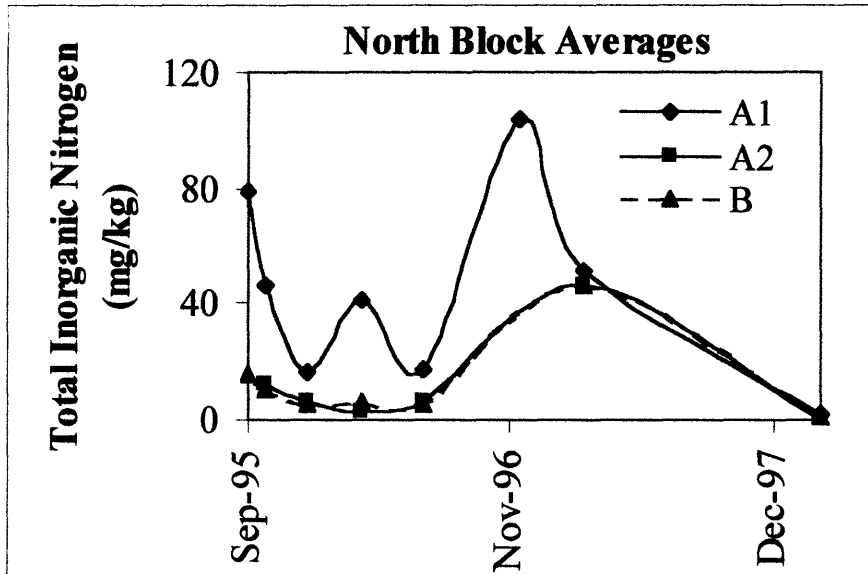
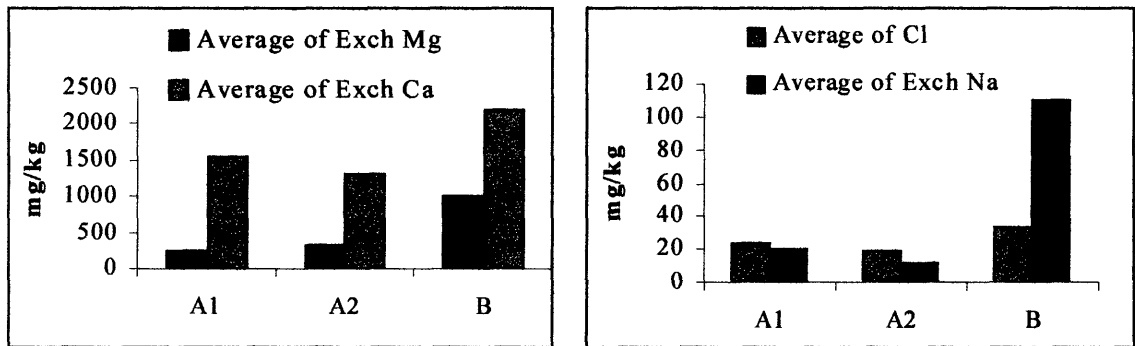**Figure 6.18.Time Series of Inorganic Nitrogen in the 3 Tullimba Soil Profiles**

Figure 6.19. Nutrient Concentrations that Increase with Increasing Soil Depth

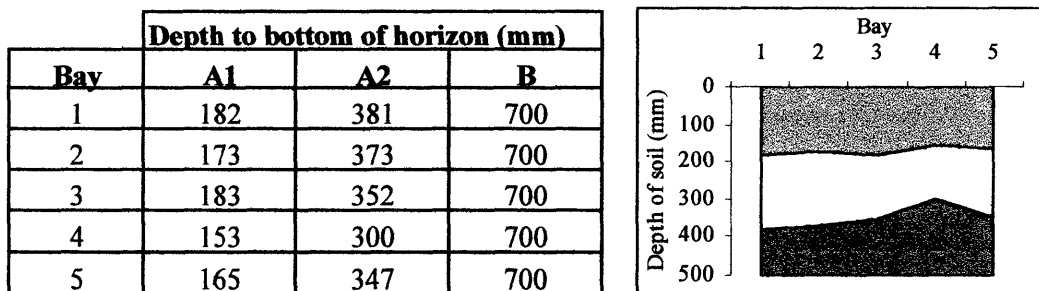|	Depth to bottom of horizon (mm)		
Bay	A1	A2	B
1	182	381	700
2	173	373	700
3	183	352	700
4	153	300	700
5	165	347	700

Figure 6.20. Average Depths over each Irrigation Bay (Pooled North and South Data)

The evaluation runs of the EMU model (Chapter 7) use data from the bay at the top of the southern irrigation block (bay 5), with the average depth for each horizon in bay 5, shown in Figure 6.20, used as input. For these runs the wilting point and field capacity were found from the average values in Table 6.10. Because there have been no measurements made on the saturated moisture content of the soil, an estimate of double the field capacity moisture content for each horizon is used (Brady 1984). The values used as initial input to the model are shown in Table 6.11.

Table 6.11. Soil Moisture Characteristics used in Initial Model Run

	A1	A2	B
Wilting point (mm)	20	31	59
Field Capacity (mm)	45	53	77
Saturated Water Content (mm)	91	106	153
Saturated Hydraulic Conductivity (mm/day)	650	82	46

6.6.2   Initial Soil Nutrients

Soil soluble cation concentration data were collected for the EIS in January 1993 (Aquila Agribusiness Pty Limited 1993) and subsequent soil analyses only considered the exchangeable component, of which the soluble component is part. Because of this lack of data for the soluble component, another avenue of estimating the soil solution concentration was investigated. As the terminal pond is suspected to capture some lateral flow above the top of the B-horizon, the concentration of the nutrients in this solution could also reflect the relative concentration of the nutrients in solution in the top layer of the soil in the irrigation area.

Irrigation did not commence at the feedlot until 19th September 1995. Three water samples were taken from the terminal pond before this date on the 15th August 1995, 4th and 12th of September 1995. These samples are used to provide an estimate of cation concentrations in the soil solution, before the commencement of irrigating with the effluent. The averages of the three samples are used as the initial soil solution values.

The adsorbed cation concentrations were found from soil samples analysed for the exchangeable cations on the 12th September 1995. Three samples from each horizon in bays 1, 2 and 3 in the North block were averaged and used as the initial values in the model.

The soil samples collected on the 12 September 1995 were also used to determine the starting values for the soluble and adsorbed forms of N and P. Organic N and P are modelled as the adsorbed form and inorganic as the soluble form. Soluble P values are determined from Bay 1 test data and the adsorbed P is the difference between the total and the soluble P. There were no samples taken from the A2 horizon on the 12 September 1995, and A1 horizon data was used for the initial A2 horizon values. The starting values obtained from the database are shown in Table 6.12.

Table 6.12. Starting Values for Adsorbed and Soluble Nutrients

	Adsorbed					
Horizon	Na	K	Ca	Mg	N	P
	mequiv/100 gm				mg/kg	
A1	0.16	0.61	5.34	0.99	1828	1194
A2	0.16	0.61	5.34	0.99	1828	1194
B	0.31	0.17	4.70	2.07	461	452
	Soluble					
Horizon	Na	K	Ca	Mg	N	P
	mequiv/100 gm				mg/kg	
A1	0.244	0.004	0.015	0.021	78.6	12.9
A2	0.244	0.004	0.015	0.021	78.6	12.9
B	0.457	0.001	0.013	0.045	15.3	1.3

Other input data required for the soil is the soil bulk density. Values used are taken from the EIS (Aquila Agribusiness Pty Limited 1993) and are 1.58, 1.75 and 1.81 Mg/m^3 for the A1, A2 and B horizons respectively.

6.7 Nitrification Model

Mineralisation of manure N is a function of both manure and soil type (Chae & Tabatabai 1986), and several authors have presented decay series for the mineralisation of manure as a function of time. Gardner *et al.* (1994) reported several series based on the N content of the manure. For manure with 1.5% N, Gardner *et al.* 94) estimated that 35% of organic N will be mineralised to inorganic forms in the first year, with 15%, 10% and 5% being mineralised in the subsequent three years. For manure having 1.0% N, the estimate is 20% in the first year, with 10% and 5% of the residual N in years 2 and 3 respectively (Gardner *et al.* 1994). For manure with a higher N content (2.5%) the decay series given by Gardner *et al.* (1994) is 40%, 25% and 6%. Powell (1997) however, estimated mineralisation ranges from 30 to 70% in the first year, 10 to 15% in the second year, followed by slow release of the residual organic N in subsequent years. Another study by Gilmour *et al.* (1977) found 41% of N in dry steer manure was mineralised in the first year and 25 % in the second year.

In the EMU model, a first-order exponential equation is used to describe the mineralisation process (Chae & Tabatabai 1986; Scott *et al.* in press). Various first-order rate constants are reported by Scott *et al.* (in press) based on the amount of residual organic N, the temperature and moisture content. At present the EMU model includes mineralisation as a function of time since application only and the first-order rate constant used in the model is a function of the N mineralised as a percentage of the original addition. The Excel Solver function was used to determine which constants gave the required mineralisation on an annual basis. The First-order rate constants that mineralised 37% of organic N in the first year, then 15%, 24% and 32% of the residual in subsequent years are shown in Table 6.13 and the rate of mineralisation is shown in Figure 6.21. These constants are used in the EMU model.

Table 6.13. First-Order Rate Constant used in Nitrogen Mineralisation Function

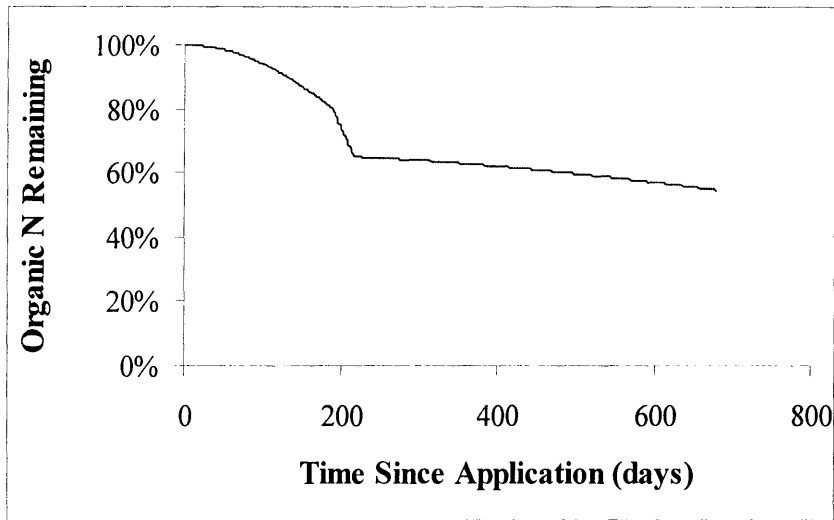| Percentage of nitrogen mineralised	First-order rate constant
80	0.0000124
65	0.0000364
0	0.0000008

Figure 6.21. Mineralisation of Manure Organic Nitrogen

6.8   Summary

The majority of input data to the model developed in this chapter are empirical. They are derived from sampling statistical distributions, or from relationships observed in collected data. Table 6.14 to Table 6.17 summarise the methods for determining these data values.

Table 6.14. Statistically Derived Manure and Effluent Variables

	Dependent Variable	Independent variable	Intercept	slope	Unit
Manure	P	Al	1.0	-0.7	dry matter %
	K	Al	1.6	-0.9	
	Na	Al	0.3	-0.2	
	N	$\sqrt{K}$	-1.1	2.5	
	Ca	Al	2.6	-1.8	
	Mg	Log(P)	0.7	1.0	
Effluent	Na	EC	-5.4	111.4	mg/L
	Mg	EC	5.6	23.7	
	Ca	Mg	1.2	1.0	
	K	Mg	-10.2	3.5	
	Organic N	Inorganic N	-0.1	1.4	
	ortho-p	Organic P	0.4	0.9	

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Table 6.15. Statistically Sampled Effluent Variables Sampled from Lognormal Distributions

Variable	Average	Standard Deviation	Units	Total Rain Previous 5 Days (mm)
Effluent EC	-0.68	0.37	dS/m	< 15
	-0.95	0.46	dS/m	> 15
Effluent Inorganic N	-0.03	0.89	mg/L	< 20
	0.11	1.43	mg/L	> 20
Effluent Organic P	1.80	1.00	mg/L	< 10
	2.05	0.62	mg/L	>10

Table 6.16. Statistically Sampled Manure Variables Sampled from Normal Distributions

Variable	Average	Standard Deviation	Units
Dry Matter	0.70	0.20	%
Aluminium Concentration	0.80	0.27	%

Table 6.17. Variables Determined from the Generation of a Random Number

Variable	Source	Units
Probability of Rain	Probability of x continuous rain days	
Rainfall Amount	Monthly rainfall distributions	mm
Evaporation Amount	Monthly evaporation distributions	mm