Predicting the impact of climatic variability on deep drainage under dryland agriculture

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EXTENDED ABSTRACT

Dryland salinity in southern Australia is caused by increased deep water losses (deep drainage) under annual crops and pastures that replaced the original perennial vegetation. Phase farming, in which lucerne, a perennial pasture with a deep root system, is grown in rotation with annual crops is a promising option to reduce deep drainage. The lucerne phase extracts soil water from below the rooting depth of annual crops, preventing its loss to the groundwater, and creating a buffer which refills again under annual cropping. The optimal length of the phases is variable and depends strongly on rainfall. Basing phase change decisions on a measurement of soil water below the root zone of annual crops (tactical management) is expected to optimise phase lengths, reducing drainage and maximising the time under (more profitable) cropping.

Computer simulations are the only practical way to evaluate the benefits and risks of such a system as year-to-year variability of deep drainage under these systems is high. It is important, however, that the effect of climatic variability is fully explored. Simulations of agricultural systems usually use an historical climate record, implicitly assuming that this captures climatic variability adequately. For stream flow and flood prediction purposes, the historical climate data record is usually not considered long enough to describe the variability that may be experienced. Stochastic data generation is therefore employed to capture more of the variability contained in the historical climate record.

We explored the effects of climatic variability on deep drainage under dryland agriculture using two different methods to capture this variability: the 48-year historical climate record and multiple records generated by a daily stochastic climate model.

Using a stochastic climate model demonstrates the potential variability in average annual rainfall. While the overall average (557 mm) matched that of the 48-year historical record (553 mm), the 48-year averages for individual generated records ranged from 495 to 627 mm.

Deep drainage under dryland agriculture is a complex and non-linear process. The simulations showed that the ordering of years in a climate record affected the predicted drainage due to carry-over effects from year to year. Predicted average annual drainage under annual cropping varied by 20% when specific patterns of wetter and drier years were created by manually reordering the years in the historical climate record. With stochastically generated climate input, the predicted average annual drainage varied even more, due to a strong relationship between average annual drainage and average annual rainfall, which is not constrained to the historical average, as it is for the manually reordered records.

Introduction of a more complete description of the potential climate variability by using stochastically generated records when simulating the outcomes of using a fixed rotation and tactical management of lucerne resulted in a different evaluation of the options. The outcomes predicted using the historical record rarely coincided with the average of outcomes predicted using the stochastic climate records. It also resulted in an understanding of the probability of different outcomes, not possible from using the historical record alone.

We conclude that when outputs are a consequence of the combination of crop type and climate over a number of years a better representation of the variability of the climate-soil-vegetation system is required than can be obtained using the historical climate record alone. The use of stochastically generated climate input into multiple simulations allows a better understanding of the potential outcomes and their probability of occurrence, while preserving the inherent nature of the historical record.

1. INTRODUCTION

Vegetation change is the accepted cause of increasing river salt concentrations and the salinisation of millions of hectares of farm land in Australia. Replacement of perennial native vegetation by annual crops and pastures following European settlement has altered the water balance causing increased groundwater recharge and mobilising the naturally saline groundwater. Deep drainage (the loss of water below the root zone of the vegetation) is the source of the additional recharge. Considerable effort has gone into quantifying deep drainage under different vegetation types and finding management systems that reduce it.

A promising option in the 300-600 mm rainfall zone is phase farming, in which lucerne, a perennial pasture with a deep root system, is grown in rotation with annual crops. It is based on the idea that the lucerne phase extracts water from the soil below the root zone of annual crops, preventing its loss to the groundwater, and creating a buffer which refills again under annual cropping.

The effectiveness of such a system has been tested in a number of experimental field studies (e.g. Ridley et al. 2001; Ward et al. 2002). These studies are, however, limited by the range of climatic conditions experienced during the measurement period (typically 3-5 years). Simulation analyses using longer historical climate records have been used to extend these studies and incorporate more variability in climatic conditions (e.g. Zhang et al. 1999; Verburg and Bond 2003).

Simulations using 40 to 50 year historical climate records may not be long enough to capture the stochastic nature of these systems. For stream flow and flood prediction, the length of historical climate data is usually considered not long enough to describe the potential variability that may be experienced during the life of a water resources project. Stochastic data generation based on the statistical characteristics of the historical data has therefore become an important tool for water resource planners to evaluate proposed system designs more thoroughly.

A range of models for generation of rainfall and other climate data is available (see review by Srikanthan and McMahon 2001). In Australia the CRC for Catchment Hydrology has developed the Stochastic Climate Library (SCL) - a library of stochastic models for generating climate data at different time scales (Srikanthan and Chiew 2003, 2005).

There is no reason to believe that drainage behaviour under dryland agriculture is less influenced by climate variability than runoff and stream flow, but simulations of agricultural systems are most commonly carried out using only historical climate data. Stochastic climate generation has been employed, but generally only where historical daily climate data were lacking or to study the impacts of climate change scenarios (e.g. Wilks 1992; Semenov and Porter 1995).

The implicit assumption that simulations with historical climate records capture climatic variability to a sufficient extent does not appear to have been tested for agricultural systems. In this paper we, therefore, explore the effects of climatic variability on deep drainage under dryland agriculture using two methods to capture this variability: the 48-year historical climate record and multiple records generated by the daily stochastic climate model within the SCL.

The motivating case study for this paper focuses on the effect of introducing tactical decision making in phase farming. The length of the cropping and lucerne phases in phase farming is determined by a range of agronomic and economic factors. It has been proposed that a measurement of soil water below the root zone of the annual crops may provide a trigger for timing decisions to change phase from a perspective of reducing drainage and maximising the time under cropping (Verburg et al. 2001). As computer simulations are the only practical way to evaluate the benefits and risks of such a system, it is important that climatic variability is fully accounted for in the analysis. We therefore evaluated whether simulations using an historical climate record capture the potential variability in outcomes or whether these simulations should be complemented with simulations using stochastically derived climate inputs. The analysis focussed on quantifying the impact of climatic variability rather than forecasting the impact of future climate, so climate change was not considered in this study.

2. MATERIALS AND METHODS

2.1. APSIM model

The Agricultural Production Systems Simulator (APSIM; Keating et al. 2003) has a flexible structure in which crops and major soil processes are dealt with in separate modules. Here we used a point-scale configuration with a wheat module (Wang et al. 2003), a lucerne module (Robertson et al. 2002), a water balance module (APSWIM), a surface residue module (RESIDUE2, Probert et al. 1998), and a soil nitrogen module (SOILN2, Probert et al. 1998). In addition, the operations, manager and fertilisation modules were used to mimic management actions such as tillage, sowing and harvesting. The APSWIM module is derived from the Soil Water Infiltration and Movement model (SWIM, Verburg et al. 1996). It is based on the Richards equation for water flow and the advection-dispersion equation for solute transport, which are solved numerically using sub-daily time steps. All other APSIM modules have a daily time step. We used APSIM version 2.1 patch 2, except for beta release (patch 3) versions of the crop modules. This version was satisfactorily tested against four detailed data sets by Verburg and Bond (2003). Soil properties from one of these data sets, a reasonably well drained Red Kandosol (Isbell, 1996) from Wagga Wagga, NSW, were used for this study.

2.2. Simulated dryland agriculture scenarios

Three dryland agriculture systems were analysed. The first was a continuous wheat system. Sowing of wheat was conditional on sufficient rainfall within a sowing window between 1 May and 15 June, or sown "dry" on 15 June. Wheat was fertilised with 140 kg N/ha/season (20 kg N/ha applied at sowing, the balance 60 days later) and 70% of crop residues were burned on 31 March with the remainder incorporated by tillage on 15 April. Summer weeds were allowed to germinate in response to rainfall between harvest and 15 April. The other systems were lucerne-wheat rotations. The rotation was either a fixed rotation with three years wheat/three years lucerne or a tactical one in which the change of phase was prompted by soil water status below the root zone (at depths of 1.3 m, 1.7 m or 2.1 m). Wheat was allowed to root to 1.2 m, whereas lucerne roots explored the soil to 3 m depth. Deep drainage was evaluated below the deepest roots, i.e. at 3 m.

The simulations were run for a 48-year period (1957-2004). The first five years of the simulation period were used to allow the simulation to stabilise and settle into the rotation. These years were not included in the analyses, which focused on the period 1962-2003 (42 years). In the case of the fixed rotation, this allowed 7 cycles of 6 years (three years wheat, three years lucerne). For both fixed and tactical rotations, the simulations started with first year wheat in 1962, unless otherwise indicated. Tactical management started in 1962 for the tactical simulations.

2.3. Historical climate record

The APSIM model requires daily values of rainfall, solar radiation, maximum and minimum temperatures as input. One set of simulations used historical data (1957-2004) from the Australian Bureau of Meteorology station 73127 (Wagga Wagga Agricultural Institute). These were extracted from the SILO Patched Point Dataset (Jeffrey et al. 2001; http://www.bom.gov.au/silo/).

2.4. Stochastic climate generation

A modified version of the daily climate model from the Stochastic Climate Library (SCL) (Srikanthan and Zhou, 2003; http://www.toolkit.net.au/scl) was used to obtain 100 stochastically generated records (each for 1957-2004). In this model a daily model is nested in a monthly model which in turn is nested in an annual model. It focuses on daily characteristics and generates these first. It uses a multivariate AR(1) model to preserve the auto and cross correlations of the climate data. Monthly and annual totals are formed from the daily generated data, and an adjustment procedure is used to ensure that monthly and annual characteristics are preserved. The daily climate model has been successfully evaluated using climate data (rainfall, evaporation and maximum temperature) from 10 sites located in various parts of Australia (Srikanthan and Zhou, 2003). The modified version used here also generated solar radiation and minimum temperature.

3. RESULTS AND DISCUSSION

3.1. Assessment of generated climate data

The climate at Wagga Wagga is temperate with a mean annual rainfall of 553 mm (coefficient of variation = 26%) for the period 1957-2004 (Australian Bureau of Meteorology station 73127). The data generated by the SCL model reproduced the statistics relating to annual rainfall closely (Table 1). Overall the model satisfactory preserved 29 of 35 annual statistics, 279 of 360 monthly statistics, and 272 of 312 daily statistics (including mean, standard deviation, coefficient of skewness, lag-one correlation, minimum, maximum, length of wet and dry spells and the various cross correlations; Srikanthan and Chiew 2003) of the four input variables required by APSIM.

Average annual rainfall for the 100 SCL generated climate records varied between 495 and 627 mm. The distribution of average annual rainfall of these 48-year sequences is related to the distribution of annual rainfall in the historical record. Despite the variation in average annual rainfall, each of the 100 stochastically generated records is an equally valid realisation of the climate. However, sequences with an average annual rainfall close to

Table 1. Descriptive statistics of historical and generated annual rainfall (1957-2004)

Parameter	Historical	SCL Mean	SCL 2.5%	SCL 25%	SCL 50%	SCL 75%	SCL 97.5%
Mean	552.6	557.4	516.2	538.8	556.8	573.1	613.2
Stdev	142.8	142.5	111.1	131.1	141.8	152.0	187.0
Skew	0.130	0.318	-0.219	0.090	0.290	0.519	1.170
Corr	0.026	0.004	-0.257	-0.062	0.012	0.080	0.361
Max	854.8	912.5	764.8	855.4	900.8	964.4	1123.4
Min	243.8	281.2	198.5	247.5	285.9	312.7	367.1
2-yr low	781.2	709.0	536.9	664.6	714.6	762.3	859.3
3-yr low	1202.6	1185.0	920.4	1128.0	1200.7	1259.6	1408.8
5-yr low	2227.9	2193.1	1896.1	2090.5	2198.3	2297.9	2531.6
7-yr low	3270.7	3233.7	2797.1	3089.4	3244.4	3384.2	3684.7
10-yr low	5011.4	4840.6	4248.7	4644.0	4865.9	5034.4	5447.8

the historical mean have a higher likelihood of occurrence than sequences with an average far away from the historical mean. As this is the case, there is no need for weighting individual sequences when using the sampled sequences in simulations.

3.2. Deep drainage under annual cropping

Annual deep drainage under cropping is highly variable (coefficient of variation of 126% for the historical simulation), as a result of the interaction between the soil-crop system and the already variable (inter-annual and intra-annual) rainfall. Comparing the two methods of accounting for climate variability, the cumulative probability functions for predicted annual drainage are similar (Figure 1). This shows that the stochastic model did not have any bias.

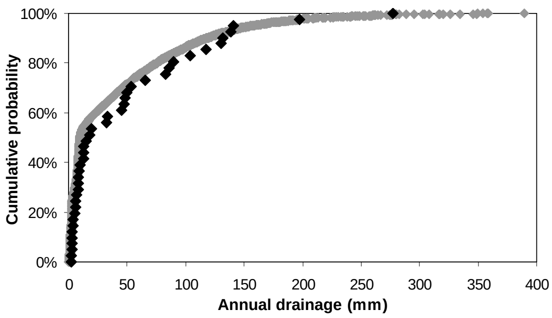

Figure 1. Cumulative probability functions of predicted annual drainage under annual cropping using the historical climate record (black) and 100 SCL generated climate records (grey).

The average annual drainage over a 42-year period (1962-2003) was highly variable for the 100 simulations with SCL generated climate records (Figure 2). It varied between 12.2 and 74.1 mm, with a mean of 40.1 mm and a standard deviation of 10.7 mm. The average annual drainage predicted for the historical simulation (48.9 mm) falls within this range as it is just one realisation of the past climate (Srikanthan and Chiew, 2005). From this we conclude that there is significantly more potential variability in average annual drainage than suggested by the use of the historical climate record alone.

A large part of this variability (77%) is explained by the variability in average annual rainfall, but it is enhanced by different sequences of wetter and drier years. Drainage is likely to be larger when a wet year is followed by another wet year than if it is followed by a dry year. This is illustrated by the predicted average annual drainage for two additional simulations in which the years within the historical climate record were manually reordered. In both cases the average annual rainfall was identical to that of the historical record. Average annual drainage was 44.6 mm for a record in which manual reordering created alternating wet and dry years, whereas it was 54.5 mm for the a record with cycles of 3 years of above average followed by 3 years of below average rainfall.

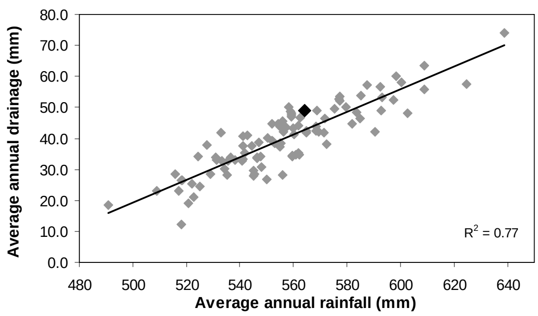

Figure 2. Predicted 42-year average annual drainage vs. average annual rainfall under annual cropping using the historical climate record (black) and 100 SCL generated climate records (grey).

3.3. Deep drainage under a fixed lucerne-wheat rotation

Drainage under a lucerne-wheat rotation was even more episodic than that under annual cropping, with most of the drainage occurring in less than 20% of the years in the fixed rotation. The coefficient of variation in annual drainage increased to 227% for the historical simulation.

Lucerne is very effective in reducing drainage during its second and third year and has an ongoing effect during the subsequent wheat phase, although the longevity of that effect depends on rainfall. This means that the amount of drainage predicted is very sensitive to how the 6 different years of the rotation (first, second, third year wheat, first, second, third year lucerne) coincide with wetter and drier years in a climate record. This is illustrated by the predicted average annual drainage of 6 alternative simulations using the historical climate record, which each started with a different crop in 1962 (Table 2). It shows that the reduction in drainage achieved by introducing lucerne in an annual cropping system can vary from 55 to 69% depending on timing of phases with rainfall in the historical record.

Table 2. Effect of the timing of phases in a fixed 6-year lucerne-wheat rotation on the simulated 42-year average annual drainage (mm) and the reduction (%) compared with annual cropping (W = wheat, L = lucerne).

	Vegetation type and year in 1962					
	1st W	2nd W	3rd W	1st L	2nd L	3rd L
Drainage	18.2	15.2	17.4	22.0	18.3	22.2
Reduction	63	69	65	55	63	55

Combining this inherent variability of the lucerne-wheat system with the variability in 42-year average annual rainfall for the 100 runs with SCL generated climate resulted in a range of 0 to 38 mm annual drainage, or 46 to 98% reduction in drainage compared with annual cropping.

3.4. Tactical phase farming

The introduction of tactical decision making in phase farming has the potential to further reduce deep drainage and/or increase the time under cropping, because it prompts a shift from annual cropping to lucerne when the soil starts to wet up and allows a return to annual cropping as soon as lucerne has dried out the soil, rather than wait for a fixed number of years. It may not always work however. Deep drainage may not be prevented if wetting up occurs after the decision has been made (on 1 March in the simulations) or if a wet year coincides with the first year of lucerne (because lucerne in its first winter-spring uses less water than annual crops, resulting in more drainage in that period).

The benefits and risks of tactical management can therefore only be evaluated over the longer term. As shown in Figure 3, when evaluated with the historical climate record (black symbol) a soil water trigger at 1.7 m depth resulted in a further reduction of average annual deep drainage of 5.5 mm (compared with the fixed rotation), while the number of wheat crops remained the same (21) in the 42-year evaluation period (1962-2003).

For the runs using SCL generated climate records the 42-year average response was highly variable due to the interaction of variability in climatic input with evapotranspiration patterns of the different vegetation types. The trend was, however, for a larger reduction in deep drainage to occur at higher average annual rainfall, and lower average rainfall to lead to more years under cropping (Figure 3).

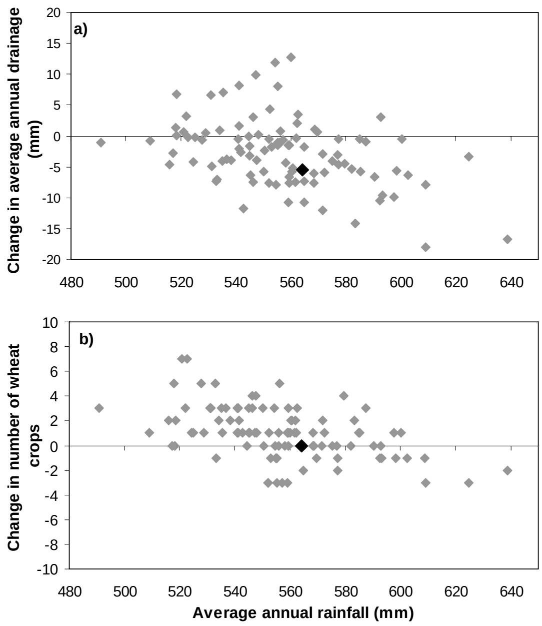

Figure 3. Simulated effect of the introduction of tactical decision making in phase farming (soil water trigger at 1.7 m depth) on (a) average annual drainage and (b) number of wheat crops grown in the 42-year analysis period as a function of average annual rainfall using the historical climate record (black) and 100 SCL generated climate records (grey).

Evaluating the soil water trigger at different depths below the root zone of the annual crops, allows one to vary the balance between a larger reduction in drainage (shallower placement) and increased time under cropping (deeper placement) (Figure 4). A more complete cost-benefit analysis would include translation of time under cropping into an average gross margin for the system as a whole, but this is beyond the scope of the current paper and will be discussed elsewhere.

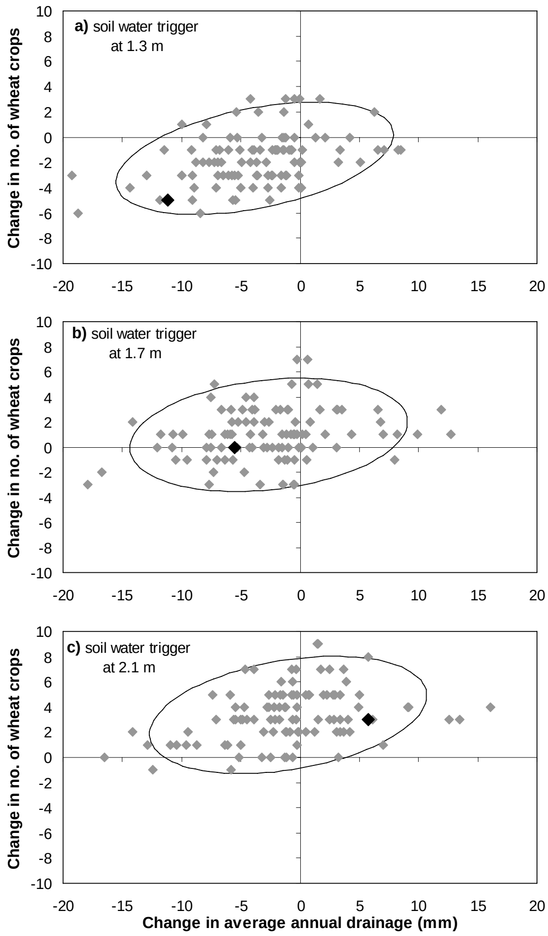

Figure 4. Simulated effect of the introduction of tactical decision making in phase farming (soil water triggers at 1.3, 1.7, and 2.1 m depth) on average annual drainage and number of wheat crops grown in the 42-year analysis period using the historical climate record (black) and 100 SCL generated climate records (grey); 90 percent confidence intervals shown also.

What is clear from Figure 4 is that evaluating the use of tactical decision making or determining the optimum depth of the soil water trigger on the basis of the historical climate record on its own could be misleading. The historical simulation predicted an increase in average annual drainage when the soil water trigger is at 2.1 m (Figure 4c). This does not seem to be the most probable result indicated by the results of runs with generated climate records. It appears the historical simulation may have had an unfavourable timing of wet years, as discussed above. Similarly, the large reduction in drainage at a cost of several crops predicted using the historical record when the trigger was at 1.3 m is almost outside the 90% confidence region predicted using SCL generated climate records (Figure 4a). It is clear that the predictions of the simulations with SCL generated climate records capture more of the stochastic nature of the system than the historical simulation alone and provide information about the probability of outcomes which is critical for the evaluation of management decisions.

4. CONCLUSIONS

Deep drainage under dryland agriculture is a complex and non-linear process. The ordering of wet periods in a climate record affects the predicted drainage due to year-to-year carry-over effects. In rotational systems with vegetation types that have different evapotranspiration patterns, the timing of the vegetation cycle relative to wetter and drier years affects deep drainage as well.

In annual cropping systems the use of only an historical record may be sufficient when simulations are used to determine the probability distributions of annual outputs. In rotational systems or when outputs are evaluated over a number of years and confidence limits are important, one needs a better representation of the variability of the climate-soil-vegetation system than can be achieved with an historical simulation alone. It is then more informative to perform multiple simulations with stochastically derived climate inputs, based on the historical data. This has the advantage of incorporating climate variability according to a chosen model, whilst also allowing for the complex non-linearity inherent within the environmental system. The generation of stochastic climate data does not add information to the historical record, but taking account of the stochastic nature of observed climate data this way is a more efficient use of the data than the traditional approach based on simulations with historical data only.

It should be noted that it is important to use a well tested stochastic climate model. In the current study the generated climate data were deemed satisfactory as most statistics were within specified relative or absolute tolerances (Srikanthan and Chiew, 2003). These tolerance limits are to some extent subjective and further verification of the statistics produced by the daily climate model in SCL may be desired.

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