Modelling Human Adaptation to Climate Variability with the Aid of an Influence Matrix

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Abstract: Human ability to adapt to climate variability may help alleviate the effects of predicted longer-term climate variability on our social, ecological and economic systems. It is not possible to model human adaptation to climate variability without considering a bewildering array of variables. The stochastic, reflexive, threshold-sensitive, time-dependent and system-wide nature of the variables usually associated with human coping and learning responses to climate variability implies the existence of a resilient-centred, complex system. The reflexive character of a resilient system especially complicates modelling approaches based on traditional deterministic and stochastic modelling paradigms. We are interested in the use of participatory game simulation models that overcome the probabilistic element of human decision-making by including it as a key variable. Our approach is based on a 2 stage-modelling project that combines the benefits of a whole-system approach with participatory modelling. In this paper we explore the role of an influence matrix in scoping, reducing and formulating the structure of a future game simulation model. Our stakeholders are farm managers from New Zealand East Coast, North Island rural communities that are currently participating in a government funded sustainable management farm study group.

Keywords: *Climate variability; resilience; influence matrix; complexity; simulation game.*

1. INTRODUCTION

Climate variability is an important driver in complex social-economic-systems (Munasinghe 2001; Peterson et al. 1997). This paper contributes to a long-term study that aims to build better understanding about the nature of human responses to climate variability in rural New Zealand. We are especially interested in the future development of participatory dynamic gaming models that can be used to simulate whole-farm-system and farm management responses to climate variability. Recent research indicates climate is perceived to be the foremost driver of farm-systems (Cole 2003). Yet climate does not act independently of other compounding factors (*e.g.* interest and exchange rates, market prices and environmental factors are strong influences on farming systems) (Peterson et al. 1997). This complexity makes the study of human response to the effects of climate variability a challenging area of research for a number of reasons.

From an ecosystem perspective (Rykiel 1985), the first challenge in this area of research is to define what we mean by a climate disturbance event (Gerritsen et al. 1985). Not all disturbances are bad (Sousa 1979) in their system-wide, temporal and spatial effects (DeAngelis et al. 1985; Pickett et al. 1989). This implies that "whole-system" modelling is needed to define and evaluate climate-mediated disturbance events in the whole-farm management context. However, such a modelling exercise requires overcoming the commensuration problems typically associated with system-wide benefit-cost analysis, and the difficulties of adequately depicting the dynamic, stochastic, time-dependent and threshold-sensitive nature of the variables we here call 'compounding factors'.

Beyond the problem of modelling system-wide effects and defining the thresholds of climate-mediated disturbance events etc., we seek to understand how and why humans respond to these events. The challenge here is that humans can respond to forecasts of climate variability in ways that change the system and therefore the validity of the prediction. Reflexive behaviour of this kind we usually associate with long-term climate variability (Walker et al. 2002). However, our point is that human response to both long- and short-term climate-change can alter the nature of a climate-mediated disturbance event. In summary, climate-mediated disturbance events in human-managed primary production systems are extremely complex in their structure, internal dynamics and behaviour. The management of such a complex system is clearly resilient-centred (Walker et al. 2002).

There are several modelling paradigms that could be used to portray complex systems of this kind, and most are capable of blending deterministic and stochastic influences. However, the problem of how to include human decision-making as a system variable is the greatest challenge. Individual human responses are themselves perception and learning mediated and can be modified by crisis-initiated innovation and intuition.

Gaming simulation models (Costanza et al. 1993; Sterman 1989) help to overcome the probabilistic nature of human decision-making by including it in each time step of the model. By doing this, the modeller is better able to assess the degree to which human perception, learning, intuition and innovation are elements of decision-making. Furthermore, in such a modelling environment the system-wide costs and benefits associated with management responses – intuitive, calculated, learned or otherwise – can be assessed. Feedback of this kind has the potential to provide insights that may be important in guiding farm management responses to climate-mediated disturbance events. This paper examines a method suitable for formulating such models.

The construction of farm management game simulation models is a serious challenge if we are to build functionality and realism into such models so that farm managers can identify with them. We have used an influence matrix (Vestor 1976) for involving stakeholders directly in the whole-system model-building process (Cole 2003). Participatory modelling is a good solution, but it can require a significant time commitment that stakeholders are not always in a position to make. Another problem we have found is that some stakeholders are not able to be actively involved in participatory modelling processes for other reasons including: accessibility and poor education. In the development of our participatory modelling research with an influence matrix (Cole 2003) we need strategies for dealing with these sorts of situations.

In this project we begin to test an alternative to the direct involvement of stakeholders in the model-building process. Our stakeholders (2 study groups of farm managers) have provided a wealth of information through dialogue-based workshops. One group has accessibility and time constraint problems. As an alternative, our research team members offered to build an influence matrix using the information the stakeholders provided. We were especially interested to see if it was possible for the 4 independent members of the research team to build influence matrices that produced consistent results from the information we were given by the 2 stakeholder groups. The challenge here is to score the matrix as a stakeholder and not a researcher.

As a separate research project, the 9 members of our second stakeholder group offered to build their own influence matrices that could be used with multivariate statistics to test the significance of results produced by this dialogue-based, 'proxy' modelling approach. The results of this study will be published separately.

1.1 What is an Influence Matrix?

The influence matrix was first developed in 1975 by a group of German scientists under the leadership of Frederic Vestor in the context of a UNESCO programme[1]. The pilot study was published by (Vestor 1976). Our interest in the influence matrix stems from its potential to be used as a whole-system modelling tool. Our aim is to reduce a highly complex farm-system model, as described by farm managers, down to its essential functional parts. We accomplish this initially by aggregating common factors together, and then by building an influence matrix.

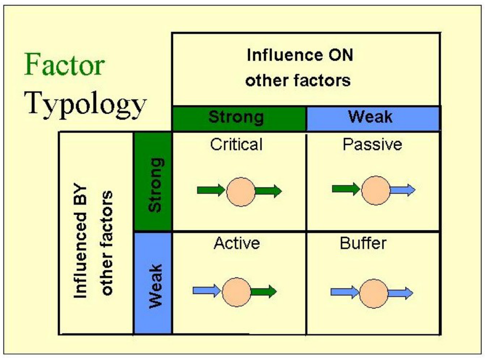

Figure 1: A factor typology

An influence matrix uses qualitative data[2] to help select, rank and understand the functional role of key system factors. It can be built in participation with stakeholders, a point that adds the benefit of model ownership on their part. The main output of an influence matrix is a typological classification of all system factors (Figure 1). We

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[1] UNESCO research programme: (Man and the Environment).

[2] The survey component of this research was conducted by members of our research team with a background in social learning and psycology.

intend to use the factor typology as a stepping-stone to formulate a game simulation model of a farm-system in Vensim – an object-oriented, system dynamics modelling software package.

The typology classifies system factors according to their functional role in the system. For example, a critical element has a strong influence *on* other system factors and is strongly influenced *by* other system factors (Figure 1). Critical factors are typically system processes that need to be managed with care because of the system-wide consequences associated with mismanagement (Vestor 1976). Yet the critical factors are not the most important in terms of developing adaptive capacity. Here we are especially interested in the identification of passive and buffer factors. Passive factors perform an important feedback-damping function. Buffer factors provide the capacity in the system that is needed to slow down and ease the approach of the system toward thresholds or limiting values.

The typology is based on information derived from the influence matrix, which quantifies the relative strength of system-wide influence for each system factor. System-wide influence is measured qualitatively with a scoring strategy of 0–5 where a score of 0 stands for no influence, 5 stands for a strong influence, 3 is an average influence, while 2 and 4 stand for lower and higher scores either side of average. The matrix is evaluated with elementary row and column mathematics that can be completed by participating stakeholders if needed.

In summary, we use an influence matrix for a number of reasons. First, it helps us to evaluate the role and relative importance of system factors. Second, it provides a systematic framework for managing complexity in a way accessible for stakeholder participation. Third, it uses the qualitative measurement of system-wide influence as a unit of account. This bypasses the theoretical and computational problems typically associated with the measurement of economic, social, ecological and cultural factors in different units. Finally, each of the critical, active, passive and buffer factors of the influence matrix typology has a direct analogue in system dynamics stocks and flows modelling (Table 1). Furthermore, they provide an important starting point for exploring adaptive functionality in the system.

Table 1 A comparison of model terms

Influence Matrix	System Dynamics
Critical	Processes
Active	Drivers
Passive	Stocks
Buffer	Flows

2. METHODOLOGY

The process involved in building an influence matrix has 5–6 clearly defined steps that can be varied to suit the specific needs of different modelling projects.

1. Factor selection
2. Factor aggregation
3. Form an influence matrix table
4. Fill in the table using influence scores

The four-team members working on this project scored their own influence matrix based on the knowledge we had gained over a period of three 2-day workshops with stakeholders. One of our social researchers also conducted a series of one-to-one interviews with farm managers. The team members discussed the information they had gathered, and insights were recorded in the form of tables and notes shared between team members. We compared the 4 influence matrices for consistency of results, resolved differences and then asked our participating farmers to check a composite model (Table 2 shown after references) to identify scores they felt were unexpected.

The numerical evaluation of the influence matrix (M_{ij}) is accomplished with elementary row and column mathematics undertaken using a Microsoft Excel spreadsheet program. First, we sum the rows (i) and columns (j) of the influence matrix to calculate the active (1) and passive sums (2). The active and passive sum scores can be used to rank the list of factors to provide insight into those highly scored factors that have the greatest influence on the system.

$$\text{Active Sum (AS)} = \sum_{i=1}^{i=15} M_{ij} \tag{1}$$

$$\text{Passive Sum (PS)} = \sum_{j=1}^{j=15} M_{ij} \tag{2}$$

The factor typology is developed using three lines of numerical information. First, we calculate the absolute numerical difference (AND) between the AS and PS scores.

$$\text{Absolute Numerical Difference (AND)} = AS - PS \tag{3}$$

As the AND score approaches zero, the functional character of a factor tends towards being critical / buffer (ref. Figure 1). By contrast, an AND score that tends towards higher values indicates the functional character of a factor tends towards being passive or active. We use the AND score to help decide the character of factors that have borderline quotient and multiplier scores.

The quotient score is used to identify the existence of active and passive factors. It is calculated by dividing the AS by the PS (4). We use the quotient score to rank our list of factors. High quotient scores indicate active functional character (a strong influence on other factors). A low quotient score indicates passive functional character (the factor is strongly influenced by other factors compared with the strength of its influence on other factors). Factors with intermediate quotient scores will tend to be more critical and buffering in functional character. We use the AND score to decide borderline cases.

Quotient Score (QS) = AS / PS (4)

The multiplier score is used to identify the existence of critical and buffer factors. It is calculated by multiplying the AS by the PS (5). We use the multiplier score to rank our list of factors. High multiplier scores indicate critical functional character (a strong influence on other factors and strongly influenced by other factors). Low multiplier scores indicate buffering functional character (the factor is weakly influenced by other factors and has a weak influence on other factors). Factors with intermediate multiplier scores will tend to be more passive and active in functional character. We use the AND score to decide borderline cases.

Multiplier Score (MS) = $AS \times PS$ (5)

For comparative purposes, we formed tables of each team member's scores that could be used to cross-check the consistency of our results. The final factor typology, which emerged as the product of this cross-checking, was then used to formulate a conceptual model of our farm system, which in turn will form the basis of a future dynamic game simulation model.

3. RESULTS

An influence matrix produced by Team Member 1 with its AS and PS scores is shown in (Table 2 shown after references). We use the AS and PS scores from the influence matrix to calculate the AND, QS and MS scores as listed in Table 3. Table 3 contains a list of the 15 aggregated factors, ranked according to their quotient scores (QS). Note the numerical pattern that this causes in the absolute numerical difference scores (AND) in column 4 of Table 3.

Table 3 The classification of factors using the AND, QS and MS scores.

Factor	QS	MS	AND	Type
Event Characteristics	1.92	1200	26	Active
External Drivers	1.23	1178	11	Active
Net Farm Income	1.15	4270	10	Critical
Farm Management	1.05	3538	3	Critical
National Effects	1.21	1320	6	Buffer
Regional Effects	1.04	2115	2	Buffer
Resilient Design	1.00	3969	0	Buffer
Results of Flooding	1.00	2304	3	Buffer
Adaptations	0.96	2915	2	Buffer
Results of Drought	0.95	2860	3	Buffer
Ecol./Environmental	0.91	2964	5	Buffer
Coping Mechanisms	0.76	2655	14	Buffer
Farm Merchandisers	0.76	1813	12	Buffer
Institutions	0.69	1395	14	Passive
Local Effects	0.46	1056	26	Passive

Another useful way of evaluating the results of the influence matrix is to rank the AS and PS scores. We have ranked the AS scores and recorded these in Table 4. The active sum is calculated as the sum of the row influence scores for each factor. The AS tells us the relative influence a factor has on all other factors in the system. It should perhaps come as no surprise that our study showed that the Net Farm Income Factor provides the strongest influence on all other farm system factors. Close behind this factor is System Resilience and Farm Management. Human coping responses to drought and flood impacts have only an intermediate to low AS ranking compared with Adaptations, which scores next with the top 3 most highly scored AS factors.

Table 4 Ranking of the active sum

Factors Ranked by Active Sum	AS
Net Farm Income	70
Resilient Design	63
Farm Management	61
Adaptations	53
Results of Drought	52
Ecol./Environmental	52
Results of Flooding	48
Event Characteristics	48
Regional Effects	47
Coping Mechanisms	45
National Effects	40
External Drivers	38
Farm Merchandisers	37
Institutions	31
Local Effects	22

Finally, Table 5 provides a comparison of the typologies produced from the influence matrices of our different team members. We used this Table as the basis of checking for consistency between our results.

Table 5 A comparison of team member results

Factors	TM1	TM2	TM3	TM4
Adaptations	B	B	B	B
Coping Mechanisms	B	B	B	B
Results of Drought	B	B	B	B
Ecol./Environmental	B	A	B	A
Farm Management	C	C	C	C
Net Farm Profit	C	C	C	C
Results of Flooding	B	B	B	B
Event Characteristics	A	A	C	A
External Drivers	A	A	P	B
Farm Merchandisers	B	P	B	P
Institutions	P	P	A	P
Local Effects	P	P	P	P
National Effects	B	P	B	B
Regional Effects	B	B	A	C
Resilient Design	B	B	B	C
Consensus (%)	NA	80	74	66

4. DISCUSSION

An influence matrix represents a snapshot of the current understanding of those who produce the scores. Our research team members (a mathematician (TM2), ecological economist (TM1), psychologist (TM4) and farm advisor (TM3)) scored individual matrices by drawing on information obtained directly from our farm study groups. The scoring of an influence table is based on consensus in a group situation. It is possible to dialogue over different scores while scoring the Matrix (a participatory approach) or by comparing results as we have done. Table 5 contains the evaluation results of the 4 influence matrices built by our research team members (TM1-4). Here we show that it is possible to get a high level of consensus between team members using this approach (see row 16 of Table 5). We have chosen TM1s Matrix (Table 2 shown after references) as a reference point for assessing consensus of results (Row 16).

According to the results of Table 2, the 2 critical factors in climate-mediated farm systems are Net Farm Income and Farm Management. Both factors are highly sensitive to system-wide feedback on the one hand and are able to exert strong influence on most other system factors. By contrast, the drivers of our model system are Climate Event Characteristics, and External Drivers. The aggregated factor, External Drivers, includes factors such as: the value of the New Zealand dollar, interest rates, tax payments, debt servicing, and public perception.

The compensatory mechanisms that help maintain a farm system in its configuration includes: Human Adaptation along with Resilient Design and Coping Responses. These 3 factors all operate through the two critical factors of Farm Management and Net Farm Income. They could be considered as styles of farm management. Our results differentiate between management style as buffering capacity and physical structures, on-farm, locally, regionally and nationally, which are capable of absorbing the effects of disturbance events.

On-farm, the stress of climate variability is absorbed by structural damage to the environment and major impacts on pasture production and stock yields. Locally, farm merchandisers are capable of absorbing disturbance events to a certain degree, beyond which regional and national effects are evident. As mentioned earlier, buffer factors are part of farm system resilience. Our analysis indicates there is a strong spatial buffering zone around farms that is needed to help absorb the shock of climate-mediated disturbance events. In contrast to the strong spatial dimension of the farm system's buffering capacity, feedback-damping functions are performed largely by local institutions (police and rescue, lawyers, accountants, schools, community groups, etc.). In stocks and flows modelling, passive factors are portrayed as stocks or indicator variables. In the context of a farm system, this suggests that the well-being of a local rural community can be included in a index of on-farm resilience.

In conclusion, our study has focused on 2 issues. Firstly, we aimed to build a consensus model of a whole-farm system that could be used as a basis for developing a dynamic simulation model. A second challenge was to accomplish this modelling aim without the direct involvement of our stakeholders in the model-building process. By getting our 4 research team members to build the influence matrix in proxy we have maintained a safeguard against individual 'modeller-bias', while demonstrating that the method is capable of producing consistent results between team members when used in this manner. Further statistical research is now needed to assess the significance of these results when compared with outcomes produced by direct stakeholder involvement in the model-building process. This paper also shows the value of an influence matrix in understanding the functional character of key factors in a complex system. While we are currently involved in further testing, the results shown in Table 5 could now be used in the formulation of a game simulation model.

5. ACKNOWLEDGEMENTS

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	Adaptations	Coping Mech.	Drought Impact	Ecol./Environ.	Farm Manage.	Economic	Flood Effects	Event Charact	External Drivers	Farm Merchand.	Institutions	Local Effects	National Effects	Regional Effects	System Resilience	Active Sum (AS)
Adaptations	3	4	5	5	1	5	5	1	1	5	3	5	3	4	5	**55**
Coping Mechanisms	5	3	5	5	3	5	3	0	1	1	3	4	2	3	4	**47**
Drought Impacts	4	4	0	5	4	5	5	2	3	5	4	4	2	3	4	**54**
Ecol./Environmental	3	4	5	5	5	4	5	3	2	3	4	4	1	2	4	**54**
Farm Management	5	5	4	5	4	5	4	4	1	5	3	3	4	4	5	**61**
Economic	5	5	5	5	5	4	4	3	5	5	5	5	5	5	5	**71**
Effects of Flooding	3	5	5	4	5	4	1	3	2	4	3	3	1	3	5	**51**
Event Characteristics	2	4	4	4	5	5	4	1	3	3	3	3	2	3	5	**51**
External Drivers	4	5	5	1	5	4	1	0	1	4	2	3	1	2	4	**42**
Farm Merchandisers	3	5	4	4	5	4	3	2	0	1	1	1	1	2	4	**40**
Institutions	3	3	1	2	4	1	1	0	0	1	4	4	2	3	4	**33**
Local Effects	2	1	1	0	2	3	0	0	1	2	2	1	2	3	4	**24**
National Effects	4	2	2	3	3	4	3	1	4	3	2	2	1	3	2	**39**
Regional Effects	4	4	4	4	5	3	4	1	3	3	3	2	3	1	3	**47**
System Resilience	5	5	5	5	2	5	5	4	4	4	3	4	3	4	5	**63**
Passive Sums (PS)	**55**	**59**	**55**	**57**	**58**	**61**	**48**	**25**	**31**	**49**	**45**	**48**	**33**	**45**	**63**	

Table 2: Example of a filled influence matrix