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Modelling climate change adaptation using cross-impact analysis: an approach for integrating qualitative and quantitative data

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ABSTRACT: Inherently, 'Climate Change Adaptation' is a complex issue requiring use of a range of methods and data, which involves many stakeholders. In this, often quantitative models relying on quantitative data are used to explore and predict the likely impact of a changing climate, and to evaluate adaptation alternatives. While such models do provide useful information, in addressing such complex issues they clearly need more data. In reality, quantitative data are not readily available, or too expensive to obtain. Therefore, to provide a more comprehensive insight, qualitative and quantitative data needs to be collected from a variety of stakeholders with different backgrounds and interests. These data are integrated for detailed analysis to transform opinions (data), into a model (system conceptualisation): especially, in the context of identifying important drivers and enablers, their interrelations, influence and dependencies. For the conceptualisation phase of such a model, the MICMAC method of structural analysis is particularly well suited for the analytical integration of culpable system parts and to identify causal feedback loops between variables. Further, the enhanced influence – dependence mapping from the method is a useful tool for the development of the resultant structural analysis to include the dynamics for a likely 'futures' scenario. In this, this paper aims to outline the systematically development of key variables integrating quantitative and qualitative data analysis into the development of a model suitable to address climate change adaptation issues.

***Keywords**:* Climate Change Adaptation; Quantitative Data; Qualitative Data; System Dynamics; Stakeholders; MICMAC Method; Scenarios

1 INTRODUCTION

Identifying climate change adaptation options and understanding the adaptive capacity to implement these options are critical for organisations or institutions involved in the adaptation process. Inherently, the identification and development of strategies to effect the adaptation of 'Climate Change' are complex issues and by nature are problematic. To develop processes and solutions to deal effectively with these complex issues requires the use of a combination and range of methods utilising data gathered from knowledgeable stakeholders, who cover a variety of differing fields, associated with climate change. In this, often quantitative models relying on quantitative data are used to explore and predict the likely impact of a changing climate, and from this, are used to evaluate adaptation alternatives. Clearly, in order to provide useful information addressing such complex issues, the model(s) needs to be developed using appropriate and relevant data.

In reality, this data comes in two forms: quantitative and qualitative. Where quantitative data are not readily available and can be difficult, or not economic, to obtain. Accordingly, in most cases, to provide a comprehensive insight for Climate Change issues, both qualitative and quantitative data need to be gathered from a variety of stakeholders. These data are integrated to enable the detailed analysis which converts stakeholder data (opinions) into an operational model (system conceptualisation), in the context of identifying important driver and enabler variables, their interrelations, and the influence and dependency between the variables. The cross-impact analysis techniques can systematically help researchers in the selection of key variables, provide for integrating quantitative and qualitative data for analysis, and enable the building of a model to address climate change adaptation issues.

MICMAC analysis was used, particularly for the analytical integration of culpable system parts and to identify causal feedback loops (both direct and indirect) between variables. Further, the Influence –

Dependence mapping from the method is a useful tool for enhancing the dynamics of the resultant analysis to allow for a likely (future) scenario. Note that discussion of the MICMAC method as used to support a combination of techniques as described below is the main contribution to this paper. To demonstrate how, we have provided extracts from two studies conducted by the authors.

In the first case, the development, using System Dynamics (SD), of a model to investigate climate change adaptation options: to assess adaptive capacity; combining stakeholder engagement; systems thinking; system dynamics and structural analysis modelling techniques, is demonstrated through reference to extracts for a Climate Change study (Sahin et al., 2013). Where, the study provides an appropriate modelling framework for assessing climate change adaptation options by the combination of SD and MICMAC modelling methods (MICMAC is the French acronym for Matrix of Crossed Impact Multiplications Applied to a Classification). This study demonstrates the use of a combination of assessment and modelling techniques, which explicitly account for the feedbacks, interdependencies, and non-linear relations that inherently characterise such systems. However, the first case doesn't exploit the full power of MICMAC. Therefore, we include a second case discussing the integration of ISM and MICMAC, in a TQM context. This case demonstrates how the full power of MICMAC could be utilised in integrating with another technique. In this, ISM analysis was used to develop the elements into a multi-level hierarchical model, and where MICMAC analysis reinforced the ranking (importance) by the power of the influences and dependencies' relationships among the applicable drivers and enablers, and how these interact as a system.

1.1 Issues for Modelling Climate Change Adaptation

It is not easy to assess the effects of various adaptation options using linear models for representing cause and effect as, generally, they are inadequate. Linear models assume that if the cause is doubled the effects would be doubled accordingly. Such thinking can be highly misleading in complex social-ecological systems where causation is driven by accumulation and feedback (Newell et al., 2011). Evidently, most environmental systems are defined by feedbacks, interdependencies, and chaotic and discontinuous non-linear relations of their elements (Kauffman, 1993; Patten and Jørgensen, 1995). In the same way, climate change is characterised by multiple interdependent components that have multiple economic, environmental, ecological and social impacts.

Faced with bounded rationality resulting from a limited knowledge about future scenarios, inadequate capabilities to handle uncertainties, and short decision timeframes, adaptation decisions are usually made during or after crisis caused by extreme events, and often not to deliver desired outcomes. In order to make an optimal decision under uncertainty, all known factors and probabilities must be taken into account. Generally, these factors are interdependent and interlinked, forming a complex feedback relationships network. Therefore, decision makers should utilise a suitable method to solve this complex probabilistic and dynamic decision problem. To do so, incorporating all key factors into modelling, requires a dynamic approach that provides much needed knowledge (or understanding) of the future behaviour of key factors in the system.

Computer models of complex systems are frequently used to support decisions concerning environmental problems. To successfully use these models, it is not enough for groups of researchers to just build and run the models. It requires not only inter-disciplinary consensus, but also participation of the applicable stakeholders. Stakeholder participation being crucial to the effectiveness of decision-making associated with adaptation management. Dietz (2003) suggests that environmental decisions must be grounded in both science, and a fair and competent public consultation process. According to Dietz, criteria for good collective decision making should include; human and environmental well-being, competence about facts and values, fairness in the process and outcome, reliance on human strengths rather than weaknesses, the opportunity to learn. The timing of stakeholders' participation in the decision-making process is essential in creating flexible adaptation alternatives. The earlier the stakeholders are involved in the process, the greater the chance of adaptation success. Throughout the modelling process, continual involvement of stakeholders in the model building, scenario development, data collection and identification of adaptation alternatives stages significantly improve the value of the resulting model usefulness, its educational potential for the public, and its credibility within the community (Korfmacher, 2001; Johnson, 2009). In this context, we employed the following approach in a combination of MICMAC and SD techniques, which was explained through a case study, to improve our understanding and ability to tackle these issues.

2 APPROACH

2.1 First Study

The model development is affected through a multi-phase process, such as: 1) Stakeholder identification and engagement; 2) Problem scoping and model conceptualisation; 3) Structural Analysis; 4) The model development, and 5) Model testing and calibration. These phases, as used in the first example, are briefly described below:

2.2 Stakeholder identification and engagement, stakeholder analysis

The aim of this phase is to identify and engage relevant stakeholders in each study area. A basic snowballing sampling technique called Hydra (Sano et al., 2010) is employed to build stakeholder networks and to select the needed stakeholders. The process starts by defining the object of potential impacts i.e. issues or elements describing ‘Assets, Operations and Community’ (AOC). A second phase is to identify climatic and non-climatic drivers, which may affect these issues/elements. The final phase is to identify adaptive responses to these impacts including, relocation of facilities, training and education of volunteers, etc.

2.3 Problem scoping and model conceptualisation.

First round for model development is organised for problem scoping and system conceptualisation, using systems thinking techniques to build a model with the support of stakeholders. At this stage, as action is pointless without a goal, through scenario building, a goal and research direction is established.

2.4 Structural Analysis - MICMAC

The first round of data analysis involves a structural analysis of the conceptual. The structural analysis process for Model development using MICMAC (Godet, 2006), as outlined below is itself a combination of techniques, used to address adaptation of climate change issues by reflecting likely scenarios model.

Scenarios are concerned with actions and the future (Godet, 1983). Where, scenarios demand an insight into the connections between relevant aspects. MICMAC is one of the standard tools of the scenario technique developed by Godet. It provided a structured process for the identification of variables for plausible scenarios for the future, based on expert judgments about systemic interactions. Where, the key to their importance is to understand the multidisciplinary connections in which combinations/variants of a disciplinary prognosis occur. As variants do not occur or fail to occur independently of each other, strategic decisions need a multidisciplinary analysis of the correlations between the relevant variables. Often, due to is limited capability of mentally processing multifactor-interdependencies by the human mind, the scenario analysis of highly complex problems needs more complex analysis methods, like MICMAC.

The strength of MICMAC in capturing interactions is used to develop and show a picture of the integrated variables: depicting them as the detailed interactions between elements of the system.

2.4.1 MICMAC - Overview

MICMAC is a tool that structures ideas into an organisational system by mapping the influence (power) and dependence relationships between constituent components (elements) of a system into a matrix of Direct Influences (MDI). In this, the tool stimulates reflection and thinking about all aspects of a group of variables as a system. Where this may be counterintuitive, but can provide further insight into visualising the ongoing consequences of current actions. Such thinking includes, for example, the ability to manage what is controllable, and not fret over what is not important. In other words, the system being modelled is considered within an ever-changing real world. Hence, through MICMAC, the model enables the review, analysis and planning for real (dynamic) scenarios. This is being essential for the innovative (intuitive) design of a desired future and, hopefully, the effective means of bringing this about (Ackoff, 1970).

The different phases of MICMAC, as described by Godet and Roubelat (1996), are: (a) Listing the Elements (variables); (b) Describing the relationship between the variables, and (c) Identifying the key variables.

Phase 1: Listing the Elements. The first stage of the MICMAC assessment lists the elements, which characterise the model under development, as well as the climate in which the model operates.

Phase 2: Description of the Relationships between Elements. In a systemic approach, an element exists through its relationship with other elements. The interrelationships of elements are captured, collated and prepared for analysis to show the relationships between these variables in a dual-entry table, as a 'Dependence/Influence Matrix' (MDI), with each cell of matrix MDI (i, j), where "i" designates the row position and "j" the column position.

In the model used by Sahin et al (2013) to demonstrate MICMAC, the MDI matrix collected responses for each pair of variables, where, if there was no relationship, a '0' was entered in the appropriate cell of MDI (i, j). However, if there was a direct influence, M (i, j) was given a '1' for low strength; '2' for medium strength; or '3' for a strong relationship.

Phase 3: Identification of the Key Elements. In Phase 3, the key elements, essential to the development of the model, are identified, first, by using the direct classification in the MDI, and then, by increasing the power of MDI, by multiplying it by itself a number of iterations, to generate a Matrix of Indirect Influences (MII).

2.4.2 Classification of Elements

Comparing the hierarchy of elements in the direct or indirect classifications can be a rich source of information. It enables confirmation to be made of the importance of the model elements/variables. The comparison also seeks to uncover other elements which, because of their indirect actions, play an important role (Godet et al., 1999).

The subjective nature of the variables (Phase 1), and that of the relationship between these elements (Phase 2), enables a group of knowledgeable people to pool their ideas, and perceptions and, thereby, reduces an individual's inevitable personal biases. In fact, as Godet and Roubelat (1996) state, in terms of the structural analysis, 80 % of the results obtained are self-evident and confirm the participants' initial intuition and, as follows, lending weight to the remaining 20% of the counter-intuitive results. Therefore, the research results (scenarios) are confirmation of the respondents' perceived reality and, through this, the wider community.

2.4.3 Direct Influences/Dependence Map

The direct influence and dependence classification of each of the elements on all the other elements in MDI are established through the paths and loops that have been established.

The model derived from MDI, and its environment, can be visualised, through the positioning of the elements on a perception map (Influence-Dependence axis). In this form of perception, each element is identified by one point on the Influence-Dependence map. The location of the position is determined by a combination of the power (influence) value as is the sum of each row in MDI (as its ordinate axis position), and its dependence value from the sum of each column of the MDI (which determines its position on the abscissa axis).

Straightforward examination of the MDI matrix sums of rows and columns show the elements that have the greatest direct impact, but do not reveal the hidden variables, which sometimes greatly influence the model. Indeed, in addition to the direct relationships, there are also indirect relationships between variables, through influence chains and reaction loops (feedbacks). A common matrix comprising several dozens of variables can include several million interactions in the form of chains and loops. The human mind cannot conceive and interpret such a network of relationships, but MICMAC does. This is achieved by the derivation of a Matrix of Indirect Influences (MII), which is derived by multiplying the MDI matrix by itself through a number of iterations to bring to light the hidden elements (indirect links).

Both the Direct and the Indirect Influence/Dependence Map are generated from the normalised sum of the Rows and Column data. The matrixes data are used to generate the Direct Influence/Dependence Map from MDI matrix, and the Indirect Influence/Dependence Map from the MII matrix. With their data normalised, these are both displayed together in Figure 1 below.

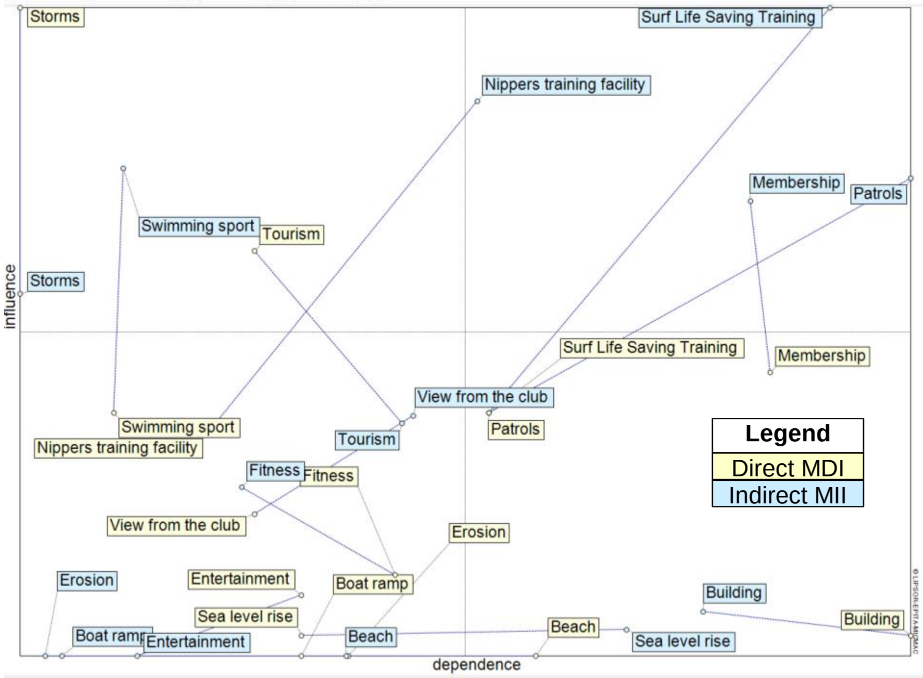

Figure 1. Example Displacement Influence/Dependence Map - Direct/Indirect

2.4.4 Analysis of Influence/Dependence Map

The obvious comparison between the Direct classification in MDI, and the Indirect matrix MII (enhanced matrix) confirm the importance of certain elements and also reveal other elements, which were previously thought to be less important, but which play a leading role because of indirect actions brought out through MICMAC.

2.4.5 Comparison of Rankings – Displacement between MDI and MII

A comparison for the Climate Change/Sea Level Rise example study elements positions show a displacement for a number of elements (Figure 2). In comparing the positions of both the direct and indirect (MICMAC) classifications on the one map has the advantage of qualifying the global, and superficial, changes in classifications.

Additionally, the quadrant and the position of the elements within that quadrant are also important criteria. However, as Godet and Roubelat (1996) suggest, the Indirect map and analysis are the more relevant in the study of 'futures' and "strategic forecasting" (Slaughter, 1990). Further analysis insight is achieved through considering the position point (Influence value the for x axis, and the Dependence value for the y axis) of the elements on the influence/dependence map being considered as a cloud of points, where the shape and positing of the elements in this cloud collectively provide a picture with respect to the various frames set around four quadrants. Where, each quadrant has a different classification for the elements in it (Godet et al., 1999).

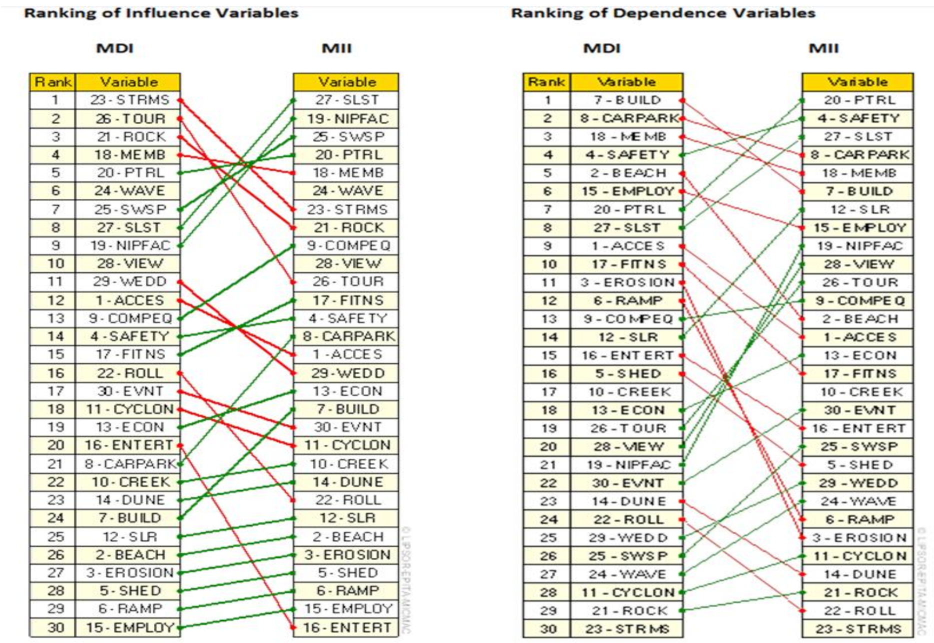

Figure 2. Comparison of Rankings Direct (MDI) and Indirect (MII)

2.5 System Dynamics Model (SDM) development

The SDM, using the platform Vensim® DSS (Ventana Systems, 2012), is built by identifying key variables, establishing causal relationships between variables and parameterising these relationships. In building the SDM, a participatory modelling approach is employed. Participatory model development focuses on showing a system structure, while model simulations reveal system behaviour, which is less intuitive and often a source of confusion (Vennix et al., 1996; Van den Belt et al., 2004; Langsdale et al., 2007). From this, a logical simulation model would be built, with a shared level of understanding and assumptions, re parameters and responses, drawn from a range of experts from academia, private consulting firms and government agencies.

The validation of any model, in the sense of establishing robust results across variations of assumptions, is important to examine whether the proposed model is realistic and useful to the users. It should answer the question: “Was the model successful at addressing its intended purpose?” That is, the proposed model matches the real-world as seen by informed observers (Sojda, 2007). This model should be validated by: 1) parameter validation; and 2) overall model validation through stakeholder engagement. Stakeholder consultation is used to assess the validity of the major components of the model by seeking agreement about: input data validity; modelling logic (i.e. parameter relationships); and ensuring the model output adequately reflects the real situation.

Overall, essential variables for model operation are identified by reviewing locally based literature for region specific inputs and examining world literature for more generic variables, and their behaviour. System norms and rules are established in combination with other literature.

2.6 Second Study: Interpretive Structural Modelling (ISM) and MICMAC Integration

In the example climate change adaptation model, outlined above, MICMAC was used in combination to develop a complex SD adaptation model that enabled the exploration of climate change adaptation alternatives. However, to demonstrate the multiple uses of MICMAC, in a study by Veltmeyer (2012) into the hierarchical nature of Total Quality Management (TQM) used ISM, another complementary structural analysis method. In this, ISM analysis emphasised the hierarchical nature of model elements, whereas MICMAC analysis reinforced the ranking (importance) of the influence and dependency’ relationships among the applicable drivers and enablers, and how these interact as a system.

In the discussion/analysis of the ISM, we are mindful of the notion of modelling expressed by Holing and Goldberg (1980), which is:

> *We would rather be roughly right about a whole system than precisely right about a trivial part of that system. A model that can be probed and explored in a simulated world becomes an evolving device of self-instruction. Its value is not so much to give answers as to generate better questions; not to define policy, but to expose some of the consequences of alternative policies.*

With this in mind, the resultant ISM modelling portrayed a set of elements at each of the six hierarchical levels that were derived through the ISM method, where the reachability set and intersection set in a matrix of element to element relationships being the same for each of the elements at that level. In that, for each of the elements sets at a level the set consists of those elements that it may help achieve (the influence/power for the element), and its antecedent set which consists of the element itself and the other elements on that level which help achieving it (dependence).

This ISM/MICMAC study findings provided empirical evidence supporting the existence of a six-level hierarchy, within which the relationships and driving power among TQM driver and enabler elements were supported, confirmed and validated to develop the TQM model as shown below in Figure 3.

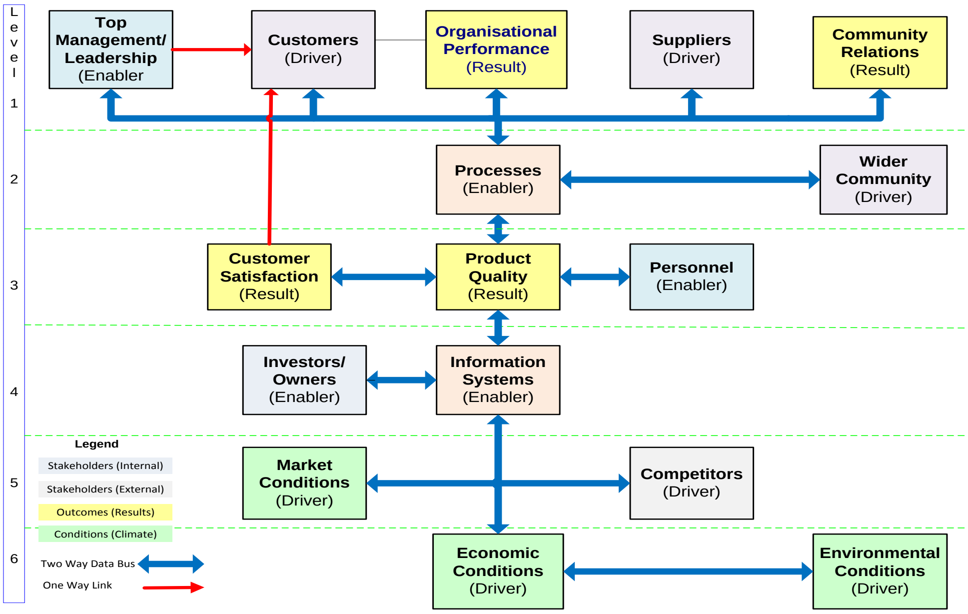

Figure 3. ISM/MICMAC TQM Model (Veltmeyer, 2012)

3 CONCLUSIONS

Dynamical concepts such as accumulation, feedback, and resilience, and the collaborative use of influence diagrams, causal-loop diagrams, and system archetypes to map out possible feedback structures, are essential elements of a practical systems approach. This is demonstrated through two examples, the first being: where SDM was used to: find the dominant feedback processes; perform sensitivity analysis in order to identify the leverage points: help in the finding of alternative strategies, which would lead to the action plan; to test and refine alternative strategies, while the MICMAC method was used to identify causal feedback loops between drivers and enablers affecting climate change, and enhance the development of likely future scenario(s). Thereby, providing a framework to improve decision makers' ability to develop alternative options for climate change adaptation management strategies, and thus respond in a timely manner to optimise resources given the various constraints. While the second example shows the integration of data to produce a multi-level hierarchical structure using ISM, which coupled with the ranking of elements by their power of influence and dependence, also using MICMAC, provided for a hierarchical model, which pictures the collective views of stakeholders as reflected in the data.

Accordingly, Structural analysis using MICMAC is capable of generating the required information about interrelationships between the key variables in a system by stakeholders. From the examples, the combination and utilisations of an array of techniques provide the potential for identifying and utilising leverage in systemic interventions.

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